WHEN INFORMED AGENTS DISAGREE

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WHEN INFORMED AGENTS DISAGREE

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I analyze the price informativeness of three informed parties' actions from 1994-2006. Consistent with their disparate environments, I find that insiders are more informative at longer (12-month) versus shorter (6-month) horizons, while analysts and transient institutions are only informative at shorter horizons. When inter-party disagreement exists, a party's informativeness is not only a function of its own strength, but also the collective weakness of its counterparts.

Using FERC, PIN, synchronicity and industry delay measures as proxies for a firm's informational environment, I find that while insider signals are unconditionally most informative, they are only predictive of future returns when prices are inefficient with respect to firm-specific information. Conversely, analysts appear unable to take additional advantage of inefficient firm-specific environments, and only appear to be predictive of future returns when stock prices are uninformed with respect to industry-specific information.

Finally, I find that the mandate of Reg FD appears to increase the power of insiders' actions, while decreasing those of their informed counterparts. This evidence suggests a decreased level of information asymmetry between individuals and professional investors, but not a lower aggregate of level of information asymmetry across the firm's informational environment.

BIOGRAPHICAL SKETCH

Sol Sean Wang was born on September 11, 1975 in Vero Beach, Florida, where lived until leaving to pursue undergraduate studies at Duke University. He graduated with a bachelor's degree as a chemistry major with an emphasis in biochemistry, then went on to pursue graduate studies at the University of South Florida where he obtained a master's degree in chemistry. Sean's background in the natural sciences garnered him a job as a project manager at Girindus Corporation, a German chemical manufacturing plant, where he was placed in charge of presenting the array of his firm's capabilities to potential Biotech and pharmaceutical clients.

As the client-based side of Sean's position at Girindus continued to pique his interest to the business world, Sean pursued an MBA at The Stern School of Business at New York University, where he specialized in Finance and graduated with highest honors. As the time at which Sean pursued an MBA coincided with the collapse of the Internet/Technology bubble, Sean became extremely interested in how irrational stock market prices could form and remain in such a state for prolonged periods of time.

This, as well as his fascination in how psychological forces could dupe investors into making poor investment decisions, eventually lead him into his pursuit of a doctoral degree at Cornell's Johnson Graduate School of Management, where he completed his degree in August of 2009. He is currently (as of 2009-2010) an assistant professor in the accounting department where he continues his research in capital markets and teaches both finance and accounting at the UNC Kenan-Flagler Business School in Chapel Hill, North Carolina.

Sean's extracurricular activities include his love for tennis, basketball, weight-lifting, cats, technological gadgets, fashion photography, exotic cars, and healthy cooking. Sean was a former competitive junior tennis player and vows to continue to refine his skills for as long as he is physically capable.

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I. Introduction

A common stock-screening strategy, often referred to as "following the smart money", consists of following the actions of professionals, particularly the trading behavior of insiders and transient institutions, and the recommendations of analysts (Damodaran, 2003).[1] Prior research documents that the actions of these informed agents predict future returns.[2] Research focused on these information intermediaries has also documented the economic incentives and behavioral biases of each group.[3] My study bridges these two areas of the literature to address the following questions: (1) How do the distinct environments of these groups affect the horizons over which their actions are most informative? (2) Given that all three parties are sophisticated and generally informative of future stock returns, what happens when there is a lack of consensus? Which signals remain informative of future stock returns, and over what horizons? (3) How do different information environments affect the hierarchy of informativeness?

Past research shows that the different pressures faced by various informed agents (e.g. incentives to generate trading commissions, incentives to avoid fund outflows, fear of litigation risk) lead to predictable differences in preferences for particular firm characteristics. The three groups of informed agents in my sample, based on 52 quarters of data from 1994 through 2006, exhibit preferences and investment philosophies consistent with past research. Analysts and institutions act as

[1] Some recent media mentions include: Business Week (2007) and MSN Money (2007) http://www.businessweek.com/investor/content/jun2007/pi20070607_123598.htm http://moneycentral.msn.com/content/P119359.asp

[2] Examples of literature focusing on the informativeness of informed signals on future stock returns include Rozeff and Zaman (1998), Piotroski and Roulstone (2004), Ke and Petroni (2004), Collins, Gong and Hribar (2003), Yan and Zhang (2007), Gompers and Metrick (2001).

[3] Examples of literature focusing on the various incentives faced by analysts, institutions and insiders include Michaely and Womack (1999), Lin and McNichols (1998), Huddart, Ke and Shi (2007), Lakonishok et al (1991), and Shleifer and Vishny (1997).

momentum chasers, while insiders act as contrarians. Because the momentum phenomenon occurs over a three to twelve month period (Jeegadeesh and Titman, 1993), and analysts and institutions appear unable to take advantage of a firm's momentum when it is in its early stages, I predict that the signals of analysts and institutions will be strongest in predicting stock returns over shorter time horizons (three to six months). Conversely, because insiders face litigation risks for trading in advance of material news disclosures and are unable to profit from round-trip trades within a six month period due to regulatory constraints, I predict that the strength of the insider signal will grow with the passing of time, and be at its peak at the 12 month time frame (versus three to six months). Results are consistent with predictions for all three groups.

To answer the second question, I compare the informativeness of each party's signal under varying circumstances of disagreement and create a hierarchy based on each signal's ability to deviate from the consensus of the other two parties and remain price informative. While insiders possess firm-specific private knowledge, insider signals may not always dominate. For example, insider sells tend to be less informative, as sales may occur due to rebalancing and liquidity reasons. In addition, because insiders must time their trades to minimize the probability of litigation risk, their trades are likely to be less informative at shorter horizons, and must be weighed against the signals from the two countervailing forces (e.g. analysts and institutions) at their optimal horizons for informativeness.

When inter-party disagreement is high, my results indicate that insiders, when buying at the 12 month horizon, are the only group able to disagree with both of its counterparts and remain as informative as a full consensus buy signal. In all other scenarios, the disagreeing signal is less informative of future stock returns than a consensus signal. The largest attenuations of signal strength come from analysts and institution sell-signals over the 12-month horizon. These results are likely to not only be caused by analysts and institutions having weaker signals at the 12 month horizon, but also because they are disagreeing with the most powerful signal, the insiders' buy, at its preferred horizon. When comparing each agent's buy or sell action across its own respective time windows, the attenuation of signal strength is smallest for insider buys at 12 months, and for analyst and institution buys at 3 and 6 months. These results are consistent with both the signal strength of the deviating agent and the signal strength of the two counterparts playing a role in determining informativeness under conditions of disagreement. Overall, results suggest the following hierarchy of signals among the three groups: insiders' actions are, on average, most informative of future prices, followed by the actions of analysts and finally, institutions.

To address the third question, I analyze how the degree of informativeness between analysts and insiders is affected by different informational environments. I use the probability of informed trade (PIN), future earnings response coefficient (FERC), industry delay (IDELAY), and synchronicity (SYNCH) as different proxies that capture various aspects of the firm's informational environment. Overall, my results from these analyses indicate that the informativeness of insiders (analysts) is conditional on the degree to which firm-specific (industry-specific) information has already been impounded into prices. For example, when PIN is low and FERC is high, i.e. when prices are more efficient with regards to firm-specific information, the insider signal becomes uninformative for predicting future stock prices changes, even at the 12-month horizon. Conversely for analysts, when IDELAY is high, i.e. industry-level information is experiencing slow diffusion into prices, the degree to which analysts' actions are informative of future prices increases significantly at all of the measured time horizons.

Finally, I examine the effect of the passage of Regulation Fair Disclosure (Reg FD) on the relative informativeness of each agent's actions. Given that Reg FD has been shown to block private information flows from insiders to other parties prior to official disclosure dates, I hypothesize that the reduced quantity of management disclosures will hinder analysts' and institutions' ability to analyze and convert public information into an informational advantage, thereby attenuating each of their signals. Results generally confirm these predictions. Consistent with the facts that: (1) a lowered frequency of disclosures may decrease the firm-specific informational environment and (2) results of my prior analyses indicating that the insider' signal is strongest when firm-specific information is most weakly impounded into prices, I find that the predictive ability of the insider signal is amplified in the post Reg FD era, raising question as to whether Reg FD has truly reduced the overall level of information asymmetry within the marketplace.

The remainder of my paper is structured as follows. Section II presents a brief overview of prior literature regarding financial analysts, corporate insiders, and institutional investors as information intermediaries. Section III develops predictions about each agent's ability to predict returns across different horizons. Section IV discusses the methodology of the data sources used, sample statistics, and the construction of each group's signal. Section V discusses the results of each agent's informativeness across the various horizons. Section VI peruses the differences in informational environments that affect signal predictability. Section VII examines the effects of Regulation Fair Disclosure on the signal informativeness of the three parties. Section VIII concludes and provides avenues for future research.

II. Prior Literature on Institutional Background and Incentives of Informed Agents

II.A. Financial Analysts

Currently, over 4,000 sell-side financial analysts are employed by investment banks, brokerage firms, and research boutiques. Analysts assist the price discovery process by assimilating information from management guidance, conference calls, macro-economic and industry-level analyses, and the analysis of financial statements. Since analysts are generally assigned to cover specific sectors or industries, they ultimately develop a deeper knowledge of industry and macro-economic forces, relative to their counterparts. Analysts then disclose their opinions of a specific firm via reports that include price targets, earnings forecasts, and buy/sell recommendations. The information in these reports is then consumed by both individuals and institutional investors when making investment decisions. While analyst forecasts and buy/sell recommendations have been shown to be value-relevant (Brown et al, 1987) and informative in predicting future earnings and stock prices, their actions have also been shown to be biased in certain circumstances due to a combination of incentives and heuristics. The biases in analyst actions have been documented in prior research, and in certain circumstances are likely to hinder their ability in predicting future returns.

For example, analysts have been shown to rely on heuristics, rather than the magnitude of market mispricing when issuing stock recommendations. Specifically, Jeegadeesh et al. (2004) show that the value relevance of analysts' recommendations is primarily driven by their tilt towards stocks with strong future growth prospects, prior earnings and returns. Bradshaw (2004) shows that long-term growth (LTG) and price to earnings-growth (PEG) multiples projections are far stronger determinants of an analyst's recommendation signal than the difference between a Residual Income Model (RIM)-derived intrinsic value and price, despite the fact that the LTG based method is least predictive of future abnormal returns.

Sell-side analysts also face numerous conflicts of interest that can affect the accuracy of their decisions. Michaely and Womack (1999) and Lin and McNichols (1998) show that analysts covering firms from which they also earn revenues via investment banking tend to be overoptimistic in their buy/sell recommendations relative to non-affiliated analysts for firms which are undergoing equity offerings, a finding experimentally supported by Hunton and McEwen (1997). By nature, firms in the underwriting process are characterized by high levels of expected future growth, and also add to the analysts' tilt towards growth firms. Further, prior papers document that, in addition to accuracy, the objective function of analysts includes increasing revenues for their respective brokerages through commissions from increased levels of trade. Irvine (2000) and O'Brien and Bhushan (1990) both show that increased levels of analyst coverage result in higher levels of trading volume. Malmendier and Shantikumar (2007) document that stock recommendations are strongly followed by small traders, and that analysts are overly optimistic in their attempts to generate increased trade while earning favor with management.

By and large, the literature on analysts' behavior documents (1) their predilection towards heuristic-based valuations, particularly measures related to future growth, (2) the fact that a primary source of analyst generated revenues stems from increased trading commissions, and (3) a conflict of interest with investment-banking related equity offerings (coupled with the fact that the majority of firms undergoing an equity offering are growth firms).

II. B. Corporate Insiders

Corporate insider trading occurs when officers, directors, and employees who own more than ten percent of their company's shares, buy or sell stock in their own firm. Due to their internal relationship with the firm, these individuals are privy to value-relevant information relative to outsiders, and are thereby advantaged in estimating the firm's intrinsic value (Piotroski and Roulstone, 2005). In addition, insiders possess the unique ability to use earnings management to optimally time disclosures around their transactions to avoid precipitous drops in stock prices.

Without constraints, policy-makers have realized that the firm-specific informational advantages of insiders (e.g. advance knowledge of material events such as mergers and acquisitions, joint ventures, and earnings announcements) would allow them to expropriate wealth from other parties.[4] Thus, regulators have prohibited trade on material non-public information (SEC Rule 10b5-1). In addition, litigators have levied harsh penalties on insiders convicted of exploiting the insider information to their financial benefit. Thus, insiders making trading decisions are faced with the trade-off between taking advantage of private information and the possibility of litigation, reputation, and employment costs.

Laws designed to constrain insiders from taking advantage of exclusive information appear to be at least partially successful. Huddart, Ke, and Shi (2007), find that insiders trade to avoid risks associated with regulatory actions, shareholder class-action suits, and adverse publicity, often leaving profitable insider trades on the table. If insiders do attempt to act on their firm-specific knowledge, they must do so well in advance to avoid scrutiny from litigators. Ke, Huddart, and Petroni (2003) show that insiders sell shares between 3 and 9 quarters prior to a break in a long-term

[4] While there have been heated debates on whether the legalization of insider trading would lead to enhanced market efficiency and social welfare, I have omitted such discussions within this paper as they are beyond the scope of my research.

earnings growth streak to avoid scrutiny from the SEC. By selling so far in advance of bad news, insiders forgo the additional momentum profits garnered by earnings growth prior to the break of the streak.

However, insiders' superior knowledge of future cash flows and earnings relative to non-insiders allows them to profit when markets have overreacted to stale information, without worries of violating insider trading rules. This argument is consistent with prior research documenting the profitability of the contrarian investment style of insiders (Rozeff and Zaman, 1998; Lakonishok and Lee, 2001).

Overall, while prior literature documents that insiders possess specific private and value-relevant knowledge about their own firm, insiders are forced to weigh the benefits of taking advantage of their inside information against the costs of increased scrutiny from third parties such as regulators and litigators. Prior research has shown that insiders appear to handle this trade-off in part through the timing of their actions by either (1) trading far in advance of significant news events, or (2) trading as contrarians following a market overreaction.

II.C. Transient Institutions

Institutional investors include investment companies, mutual funds, brokerages, insurance companies, pension funds, investment banks and endowment funds. In general, these firms earn their living by managing large sums of capital for investors and taking a percentage of the total assets under management, or a percentage of returns over a given benchmark. Unlike analysts and insiders, institutions do not possess an explicit informational advantage that they can leverage to inform future prices. Thus, in order to maximize their fund's performance, they combine the informational advantages of both insiders and analysts with their own analyses. They do this by augmenting their internal research with external reports from sell-side analysts, while also attempting to earn favor from upper-level management that could result in exclusive access to firm-specific information.

Overall, prior literature documents that the actions of institutional investors have predictive power for future returns, consistent with these agents being informed traders. Gompers and Metrick (2001) show that the quarterly level of aggregate institutional ownership is associated with future stock returns. While they attribute this in large part to demand shocks resulting from changes in ownership composition, Yan and Zhang (2007) show that the predictive power of total institutional ownership is driven entirely by changes in short-term institutional ownership. Their study is consistent with institutions driving returns due to them being informed investors, and not because of the demand shock as posited by Gompers and Metrick.

Recent papers focusing on the behavior of institutional investors use Bushee's (1998, 2001) classification techniques, which characterize institutions based upon their level of portfolio diversification, turnover, and trading sensitivity relative to current earnings. Each institution is classified as either a "transient", "dedicated", or "quasi-indexing" institution. Transient institutions are characterized as typically holding stakes in numerous firms, trading frequently, and often basing their trades on current earnings or components of such earnings. Of the three institutional classes, they are most likely to search for private information, as dedicated and quasi-indexing institutions have different primary objectives, and hence have little incentive to search for private information. Because this paper examines the informativeness of institutions' trading decisions, it focuses solely on transient institutions, henceforth referred to as "institutions."

Prior literature regarding the actions of transient investors has shown them to be harbingers of both future earnings and abnormal stock returns. Ke and Petroni (2004) show that these institutions appear able to predict when a firm will have a break in a string of quarterly earnings increases, and trade at least one quarter prior to this event to avoid the upcoming negative stock returns associated with the disclosure of the bad news. Collins, Gong, and Hribar (2003) find that transient institutional investors exploit the mispricing of accruals to earn abnormal returns. Similarly, Ke and Ramalingegowda (2005) document that transient institutions trade to exploit post earnings announcement drift, and document arbitrage trades that yield buy and hold annualized abnormal returns of 22%.

Despite being generally informed, institutions face constraints that can create preferences for specific firm characteristics, prohibiting them from fully utilizing their informational advantages and from optimizing their investment decisions to maximize profits. For example, the clients of institutional investors often have little or no knowledge about capital markets. The lack of market knowledge of clients providing institutional investors with capital can result in agency issues that can hurt institutions when they most aggressively attempt to exploit market mispricings. For example, if an investment manager were to purchase undervalued firms in an attempt to exploit market mispricing, his clients may only see their funds being allotted to poorly-performing firms with undervalued multiples primarily derived from deflated stock prices. Since stock price reversals often take up to three years (Debondt and Thaler, 1985), it becomes highly likely that the price will continue to drift negatively before reversing its direction.

While the optimal strategy for institutions in an agency-free world would be to trade even more aggressively to exploit the mispricing, the reality is often that investors refuse to provide additional capital to the arbitrageurs, and even remove capital in fear that they may lose their investment. This separation of "brains and capital," as referred to by Shleifer and Vishny (1997), can prohibit arbitrageurs from exploiting long-term mispricings (e.g. value stocks) that may worsen in the short-run, as negative returns can lead to investment outflows when capital is most needed to exploit such mispricings. In attempts to avoid these fund outflows, mutual funds (O'Neal, 2007) and pension funds (Lakonishok, et al. 1991) have been documented to engage in "window dressing," where firms sell large positions in poorly-performing stocks and buy large positions in stocks with strong past returns prior to the quarterly and yearly disclosure of portfolio holdings, in an attempt to keep individual investors from removing capital from the fund.

In addition to the "window dressing" problem, institutional investors are often constrained by the fiduciary responsibilities they have to prudently invest their customers' capital. Farber (2005) shows fraud to be linked to decreases in institutional ownership which are not reversed despite improvements in corporate governance. He attributes the lack of increase in institutional ownership to the fact that most institutions limit their investments to firms which are deemed to be financially sound. Such fiduciary restrictions also limit institutions from pursuing value strategies, often composed of purchasing poor past performers, where markets may have overreacted to bad news.

Finally, the sheer volume of shares transacted by institutions on a per trade basis also creates a preference for firms with higher levels of liquidity, to reduce transaction costs and adverse price impacts caused by information asymmetries with the market-maker (Glosten and Milgrom, 1985). In order to be able to quickly transact such block trades while minimizing price concessions, institutions prefer liquid stocks with higher turnover levels, while avoiding low-priced firms where transaction costs can be relatively high (Falkenstein, 1996).

In sum, institutional investors face a unique environment that includes "window-dressing" issues, fiduciary responsibilities to their investors, and microstructure concerns. As a consequence, transient institutions prefer shorter-term momentum-based strategies, being net buyers of firms with extreme positive prior returns, and net sellers of firms with extreme negative returns. They are also net buyers of glamour stocks with higher market-to-book ratios, and net sellers of value stocks with lower market to book ratios. They are most likely to prefer heavily traded firms both when buying and selling, in order to avoid microstructure-based price concessions.

III. Relative Signal Informativeness at Different Horizons: Predictions

Section II presents prior literature on the differing environments of the three groups of informed agents, discussing how these differences could constrain investment decisions and create affinities toward particular firm characteristics. In this section, I use the preceding discussion to predict (1) the horizon at which each party's actions are most likely to be informative of future prices, and (2) the circumstances under which each party is likely to remain most informative when deviating from a consensus of the other two.

As discussed earlier, past literature documents the preferences of analysts and institutions for firm characteristics such as momentum and market-to-book, and the contrarian preferences of insiders relative to these two groups. A few other points are worth noting. First, insiders do not suffer from the performance based arbitrage problem faced by institutions. While both groups attempt to arbitrage mispricing in order to create profit, insider trades are financed with personal capital, often as part of their compensation package, while institutions typically exploit mispricing by using the capital of less sophisticated investors. Thus, unlike institutions, insiders are not constrained from pursuing value strategies. Second, while institutions are free to exploit short-term anomalies such as post-earnings announcement drift (Bernard and Thomas, 1990), and post-revision drift (Gleason and Lee, 2003), Rule 16(b)-6 in SEC act of 1934 prohibits insiders from profiting on any round trip trades where the holding period is less than six months. Given that momentum profits are primarily documented over short-to-intermediate time horizons, this "short-swing rule" adds another constraint to insiders wishing to execute such momentum strategies.

The above arguments, coupled with insiders' possession of superior knowledge regarding the future cash flows and earnings of their firms (Piotroski and Roulstone, 2005), suggest that insiders who trade optimally to maximize profitability while minimizing litigation risk should trade as "late-stage" contrarians, implying that they should not only trade following market overreactions, but that they should also take advantage of their superior knowledge of when a market correction is expected to occur. Since price momentum follows a market correction, and the timing of the insiders' trades should enable them to take full advantage of such momentum, I expect the insider signal to become more informative over longer horizons.

As previously discussed, both analysts and institutions prefer firms with similar characteristics. Owing to trade generating incentives, investment-banking conflicts of interest, and general biases in their valuation methods, analysts appear partial towards stocks with high-levels of future growth and strong prior price momentum. Institutions, albeit for different reasons such as performance-based arbitrage issues and "window-dressing", also share preferences for momentum and growth. Given that the momentum phenomenon has been documented to occur over a 3 to 12 month horizon (Jegadeesh and Titman, 1993), and that analysts and institutions apparently act after a firm has already exhibited signs of positive momentum, I expect the actions of analysts and institutions to be more informative over shorter horizons, leading to the following relative predictions:

- Insiders' actions are most price informative over longer (12-month) horizons, while analysts' and institutions' actions are most price informative over shorter (6-month) horizons.

Earlier discussions suggest that informed parties will not always act in tandem. How is the informativeness of each group affected when there is a lack of unanimity? To the best of my knowledge, this question remains unresolved. In a world free of insider trading constraints, insiders' private information advantages shown in past literature (Piotroski and Roulstone, 2005) would result in insider trading signals dominating those of their two counterparts, rendering the above empirical question trivial. However, due to litigation risk concerns and insider-trading restrictions such as the "short-swing rule," as previously discussed, whether insiders are consistently able to reveal their private information through their actions is unclear. Furthermore, insiders may exhibit overconfidence (Malmendier and Tate, 2005), overoptimism (Heaton, 2002), or subjective biases resulting in an overweighting of their own private information and an underweighting of non-firm specific information (Daniel, Hirshleifer, and Subrahmanyam, 1998). These factors potentially attenuate the informativeness of the insider signal. Finally, the trading horizon at which each signal is strongest must be considered. While the insider signal is expected to be relatively stronger at longer horizons, the signals of analysts and institutions should be relatively stronger at shorter-horizons. If the returns to insiders' actions are measured at their non-preferred horizon, insiders' signals may not predict future returns when opposing the two counterforces.

I base my predictions regarding the informativeness of each party's signal under conditions of inter-party disagreement on the following four premises:

i. Due to exclusive access to firm-specific information, insiders have a general informational advantage over analysts and institutions.
ii. Owing to insiders' contrarian behavior, the informativeness of their signal is expected to be stronger at longer (12-month) versus the shorter three- and six-month windows.

iii. Insiders' BUY signals are more predictive of returns than their SELL signals as insiders may sell for non-informative reasons related to liquidity, rebalancing, and taxes (Lakonishok and Lee (2001)).

iv. Analysts and institutions are momentum-style traders. Since momentum exists as a short-intermediate term phenomenon (Jeegadesh and Titman, 1993), the strength of their signals is likely to attenuate over time, and should be strongest at the three- or six- month time horizons.

The basis for whether or not each party's action is likely to be informative hinges upon two primary forces: (1) the strength of the deviating signal over a particular time horizon, and (2) the relative weakness of the countervailing forces. Overall, I predict that:

- The most probable scenario where a deviating party remains informative is when insiders are *buying* against a consensus *sell* of the other two parties, and returns are being predicted over longer horizons.
- The actions of both analysts and institutions are likely to be less informative at *longer horizons*, when they deviate from a consensus of the other two parties.
- Analysts or institutions who deviate from the other two parties are likely to have the worst outcomes when they issue *sell* signals, and returns are being compounded over the longest horizon.
- Deviating insider buy signals are still likely to be informative at shorter horizons.

The first prediction arises from the expectation that the predictive power of insider actions is strongest for *buy* signals at longer horizons, while the deviating signals from analysts and institutions are weakest at these horizons. The second prediction is derived from the argument that neither analysts nor institutions are likely to prevail against insiders at the latter's advantaged horizons. The third prediction stems not only from the same logic as the second argument, but also from the fact that the insider's informational advantage should be strongest when *buying* over the 12 month horizon. The final prediction is derived primarily from the general dominance of the insider signal, and hence, is made with less confidence, because insiders are competing against the countervailing actions of analysts and institutions at the latter's advantaged horizons.

IV. Data Sources, Signal Construction and Sample Characteristics

IV. A. Data Sources

To examine the behavior of each entity, I use quarterly data, spanning 1994-2006, from the CDA/Spectrum database (Form 13F disclosures of institutional holdings), the filings of insider trades (SEC Forms 3, 4, 5), and the Institutional Brokers Estimate System (IBES) database. The 13F form reports all institutions with more than $100 million of total holdings,[5] or with common-stock positions within a specific firm of more than 10,000 shares or $200,000. Forms 3, 4 and 5 are obtained from the Securities and Exchange Commission (SEC) Ownership Reporting System data file. This database contains transactions by all insiders who are subject to disclosure as mandated by the SEC Act of 1934, Section 16(a), which mandates the reporting of all trades by any person who is either directly or indirectly the owner of more than 10 percent of any specific equity security by the tenth day of the calendar month after the trading month. The IBES stock recommendations database dates back to 1994, and includes the stock recommendations of financial analysts, as self-reported by over thousands of brokerages from the largest global houses to smaller regional and local shops.

In order to examine returns under varying levels of disagreement, there must exist a disclosure for each signal, as well as corresponding Compustat quarterly data and Center for Research in Security Prices (CRSP) monthly files for each firm in order to control risk over the 12 month horizons. Analyses are restricted to U.S. firms listed on the NYSE, AMEX, or NASDAQ stock exchanges. After filtering for missing

[5] Other types of security holdings that contribute to the "total holdings" disclosure threshold include convertible bonds, stock options, and preferred stock.

observations, removing observations where firms do not report in consecutive periods, and deleting stocks with share prices of less than $3 to avoid undue noise in estimating returns (Conrad and Kaul, 1993), my sample set consists of 59,008 firm-quarter observations.

IV. B. Signal Construction

The analysts' signal, ANA henceforth, is constructed on a quarterly basis in a manner similar to Jegadeesh, Kim, Krische and Lee (2004), who find the consensus change in quarterly recommendations to be more informative than the consensus level of the recommendation. I reverse code the variable from each recommendation by subtracting the level of the recommendation from 5, such that a strong buy is now coded as 4, a buy is coded as 3, a hold as 2, a sell as 1, and a strong sell is coded as 0. The quarterly consensus change is taken as the difference between the mean recommendations of the current and prior quarters. If a firm does not have analyst coverage for consecutive quarters, it is removed from the sample. Each signal is then converted into a non-parametric percentile rank in order to account for the right skewness of these signals as documented by Piotroski and Roulstone (2004). In the event that two firms have the same magnitude of consensus change in recommendation, the firm's signal is considered to be stronger if its current level of consensus has a higher rank.

Because Yan and Zhang (2007) document that long-term buy-and-hold style institutional trading is not related to future stock returns, I use Bushee's (1998, 2001) institutional investor classifications[6] to parse out institutional trades by "dedicated"

[6] Bushee's classification techniques use factor analysis to characterize institutions based upon portfolio diversification, portfolio turnover, and trading sensitivity relative to current earnings, labeling them as either "transient", "dedicated", or "quasi-indexing" institutions. Dedicated institutions tend to prefer longer-term holdings and these institutions often tilt their holdings toward "prudent" stocks (Del Guercio 1996). These institutions are characterized by "relationship investing," which reduces their

and “quasi-indexing” institutions.[7] Transient investors are characterized as typically holding stakes in numerous firms (higher diversification) and trading frequency (higher turnover), often basing their trades on current earnings or components of such earnings (higher earnings trading sensitivity). The transient institutional signal, TI, is calculated as the difference in shares held by transient institutions from the preceding to the current quarter, divided by the number of shares outstanding in the preceding quarter, as reported in Form 13F. Similar to ANA, the TI signal is also converted into percentile ranks over the entire sample period.

The corporate insider signal, CI, is computed as in Lakonishok and Lee (2001), as the difference between the number of purchases and the number of sales, divided by the total number of purchases and sales, for each reporting period where there is at least one insider trade. For consistency, each signal is converted into a nonparametric variable by ranking the variable into deciles over the entire sample period. For firms with signals of -1 or +1, the signal is considered to be stronger when the dollar amount traded is larger relative to the total market value of equity for the firm at the end of the quarter.

IV. C. Sample Characteristics

Table 1 shows annual univariate statistics taken from the final sample of firms. On average, insiders appear to be net sellers of stock. This is consistent with past research, and may be because the data reported only reflects shares transacted on the open market, which are unlikely to reflect shares gifted to insiders as part of their compensation plans. Consistent with prior literature, analysts show optimism in their

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incentives to search for private information. Quasi-indexing firms have a primary objective of diversification, and are thus less likely to base their trades on information.

[7] In untabulated analyses, I partition the trades from dedicated and quasi-indexing institutions separately to determine whether their net trades are predictive of future returns, and find the informativeness of each group to be insignificantly different from zero at 3, 6, and 12-month time horizons.

Table 1. Summary Statistics of Informed Parties' Actions from 1994-2006

Year	Number of Firms	Analysts' Consensus Recommendation	Analysts' Dispersion	Change in Analysts' Consensus Recommendations	Insiders' Net Trade Ratio (Trades)	Insiders' Net Trade Ratio (Dollars)	Insiders' Net Trade Ratio (Shares)	% Change in Transient Institutional Holdings (Shares)	Disagreement as Variance of Ranked Signals (DIS)
1994	2880	2.87429	0.67856	-0.01841	-0.13545	-0.19289	-0.19439	0.98455	0.10461
1995	3523	2.85439	0.64128	-0.03638	-0.19307	-0.25623	-0.25731	1.40569	0.10565
1996	3894	2.86482	0.63577	-0.00723	-0.17583	-0.24837	-0.24937	1.52833	0.10404
1997	4232	2.95956	0.60656	-0.00871	-0.23164	-0.31142	-0.3135	1.57084	0.10286
1998	4599	2.96715	0.59594	-0.02283	-0.03688	-0.1111	-0.11507	1.51215	0.10804
1999	4554	2.96084	0.5933	-0.01062	0.02878	-0.02645	-0.02952	1.92683	0.11184
2000	4662	3.01236	0.5833	-0.01572	-0.11531	-0.16332	-0.16705	2.11555	0.11477
2001	4806	2.96515	0.58221	-0.0234	-0.3245	-0.38418	-0.38737	3.04343	0.11345
2002	4643	2.76687	0.65053	-0.10187	-0.25238	-0.31796	-0.31988	2.36067	0.12037
2003	4781	2.53314	0.70215	-0.02557	-0.46221	-0.51358	-0.51485	2.41234	0.11655
2004	5257	2.60751	0.71163	-0.00033	-0.54915	-0.60896	-0.61007	1.4074	0.10627
2005	5437	2.67948	0.71714	0.00216	-0.51549	-0.56838	-0.56993	1.67346	0.10119
2006	5740	2.67431	0.72902	-0.01676	-0.52595	-0.57093	-0.5721	0.49091	0.09733

This table provides descriptive statistics at an annual level for the firms included in the sample. The total number of firm-quarters in the sample is 59,008. The sample consists of all firms listed on NYSE, AMEX, or NASDAQ stock exchanges from 1994-2006, a total of 52 quarters, with data being taken from the CDA/Spectrum database (Form 13F disclosures of institutional holdings), the filings of insider trades (SEC Forms 3, 4, 5), and the Institutional Brokers Estimate System (IBES) database. The insider net trade ratios is calculated as the total number of purchases less the number of sells (in either shares or dollars traded), divided by the sum of shares and purchases. The change in transient institutions holdings is calculated as the difference in shares held by transient institutions from the current quarter to the previous quarter, divided by the number of shares outstanding at the end of the preceding quarter. Change in analyst consensus recommendation level is calculated as the change in the mean level of recommendation from the preceding to the current quarter. Disagreement (DIS) is calculated as the variance across decile-ranked signals after being scaled to hold a value between zero and one.

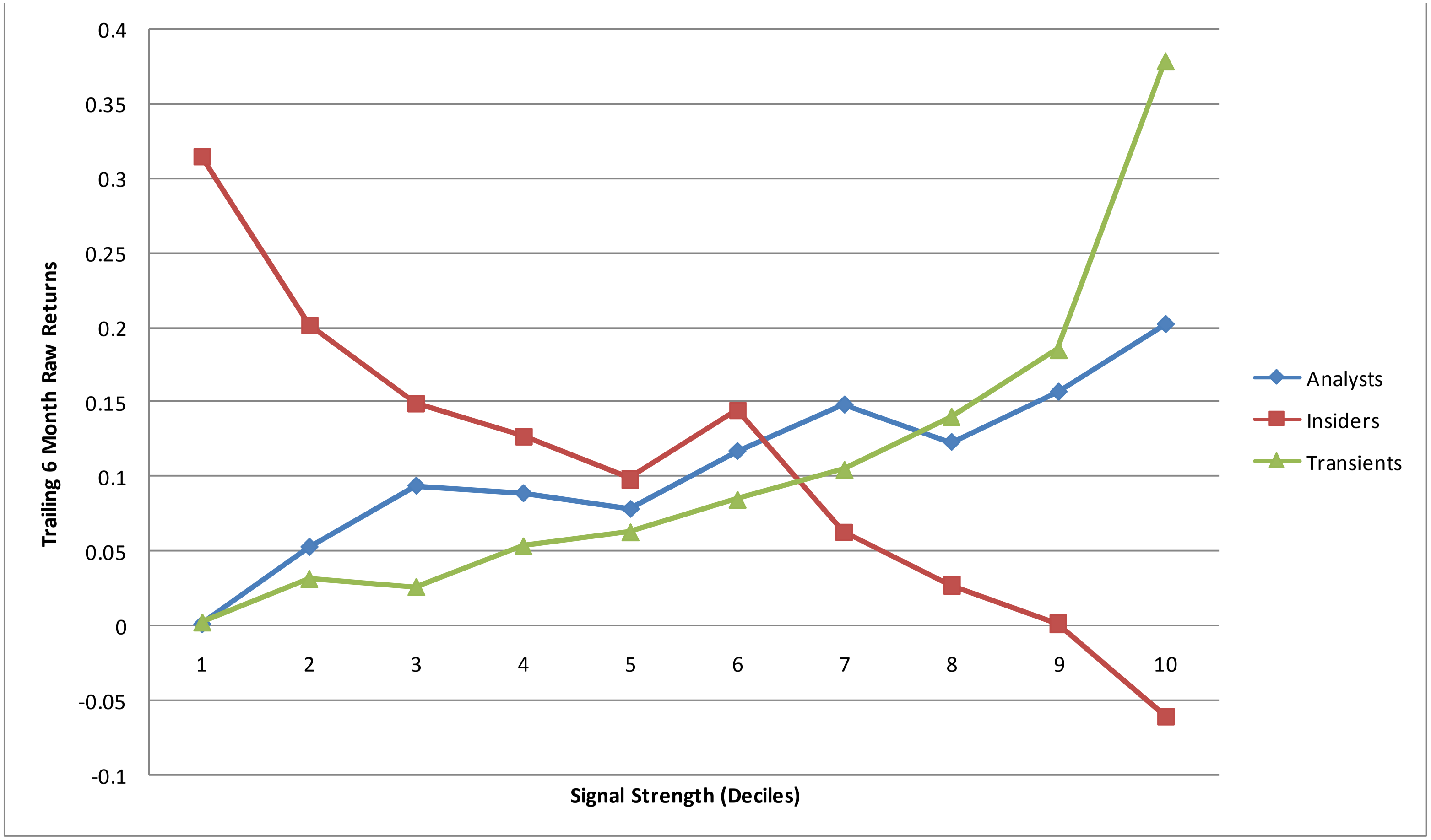
consensus, as firms on average are rated as buy firms. The change in consensus recommendation, or the level of upgrade or downgrade between quarters, is nearly zero, with the exception of the year 2002, where the average change in consensus decreases by 0.10. It is also interesting to note that the mean consensus recommendation decreases from 2.97 in 2001, to 2.67 in 2006. This decrease coincides with the passing of the Sarbanes-Oxley Act (SOX) (passed in July of 2002), which could be consistent with SOX leading to improved financial reporting quality, and a subsequent decrease in the consensus recommendation. On average, transient institutions are net buyers, reflecting the overall growth in institutional money management over time. In the far right column, inter-party disagreement is calculated as the variance across decile ranked signals, after scaling each signal such that it obtains a value between zero and one. Disagreement appears to decrease from the years 2002-2006, perhaps consistent with Sarbanes-Oxley Act resulting in improved disclosure that could decrease disagreement amongst the three parties. It is interesting to note that this proxy for inter-party disagreement is negatively correlated ($\rho = -0.29$, p-value < 0.0001) with the standard deviation of analysts' consensus recommendations, a common proxy for information uncertainty. This is consistent with inter-party disagreement stemming from the differing environments of the three parties, rather than merely general ambiguity about a firm's future. Pearson correlations (untabulated) between the informed parties' signals show that insider signals are negatively correlated with both analysts ($\rho = -0.0430$, p-value < 0.0001) and institutions ($\rho = -0.1057$, p-value < 0.0001), while analysts' recommendation changes and institutions' net shares traded have a positive correlation ($\rho = 0.0898$, p-value < 0.0001). These correlations are consistent with past literature as discussed in Section II.

Next, I examine whether each informed party's signal exhibits the preferences for particular firm characteristics suggested by past research and the discussion in Section II. Figure 1 plots momentum in the form of prior 6 month returns, against each party's signal strength, as reported by deciles. Consistent with prior literature, analysts' and transient institutions' signals are correlated with positive prior returns, and insiders appear to exhibit contrarian philosophies.[8] At the extreme deciles for BUY signals, institutions have the strongest preferences for positive momentum, followed by analysts, and then insiders. Conversely, at the extreme deciles for SELL signals the opposite is observed. Finally, note the diametrically opposed preferences of insiders and institutions for high momentum stocks. The extreme quintiles for institutional buying behavior and insider selling behavior appears strikingly similar. Institutions buy firms with returns of 2.71% compounded monthly over the prior six months, while insiders sell firms with monthly returns of 2.30%.

Figure 2 plots the market-to-book ratio, a proxy for glamour (high M/B) and value (low M/B) against the signal strength deciles. Overall, insiders exhibit the strongest buying preferences for firms with the lowest levels of market to book, while analysts and institutions exhibit a higher affinity for buying glamour firms. At the univariate level, the relative difference between institutions and analysts is largest at the extreme buying decile. Finally, the extreme insider selling decile and institutional buying decile are again similar, with insiders selling glamour firms with an average market-to-book ratio of 3.51 and institutions buying glamour firms with an average market-to-book ratio of 3.49.

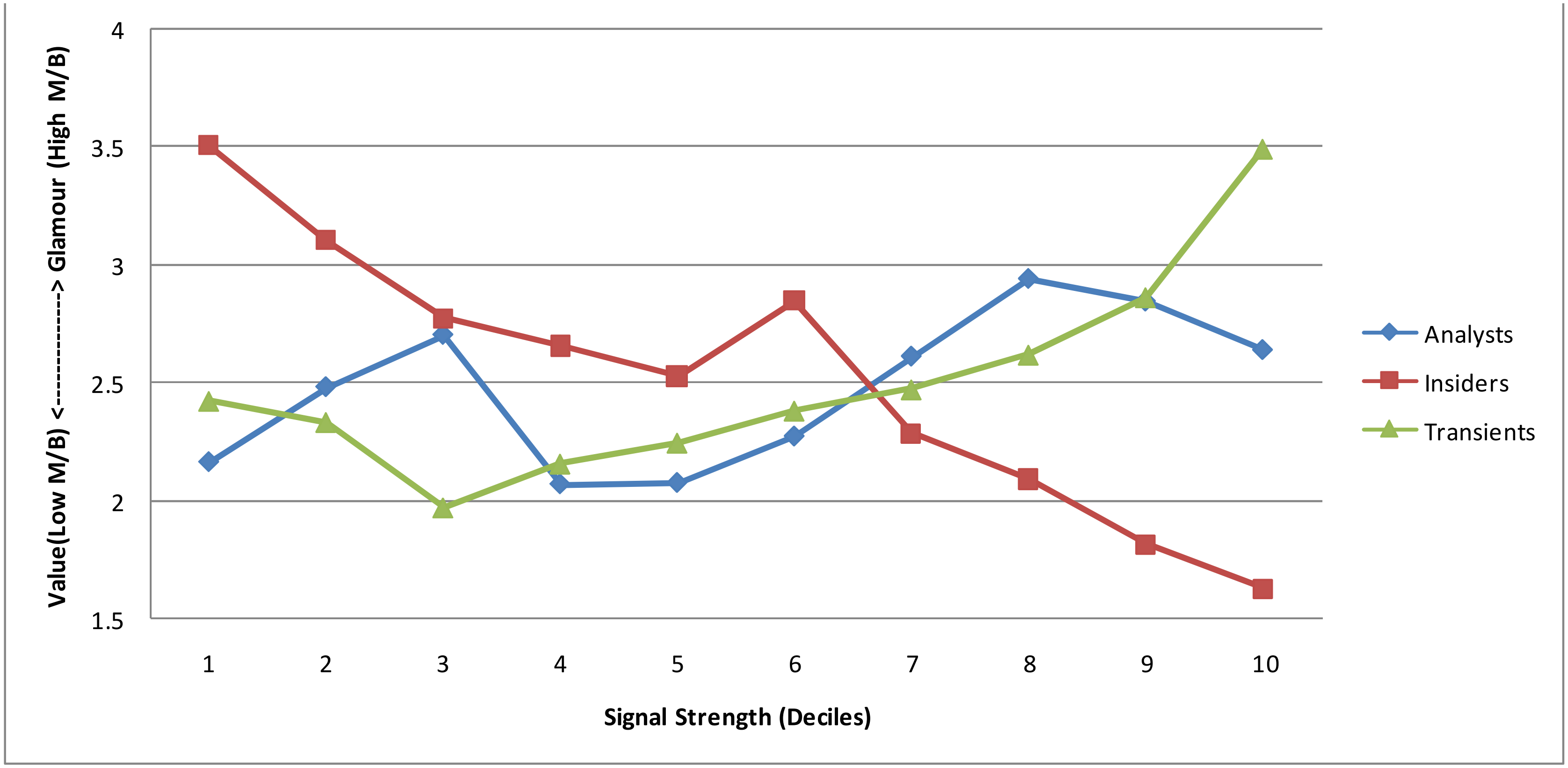
Figure 3 plots signal strength deciles against the preceding six-month total trading volume scaled by total shares outstanding. Consistent with the discussion in Section II, the buying and selling behavior of institutions suggests strong preferences

[8] 3-Month and 12-Month BHAR's show similar patterns.



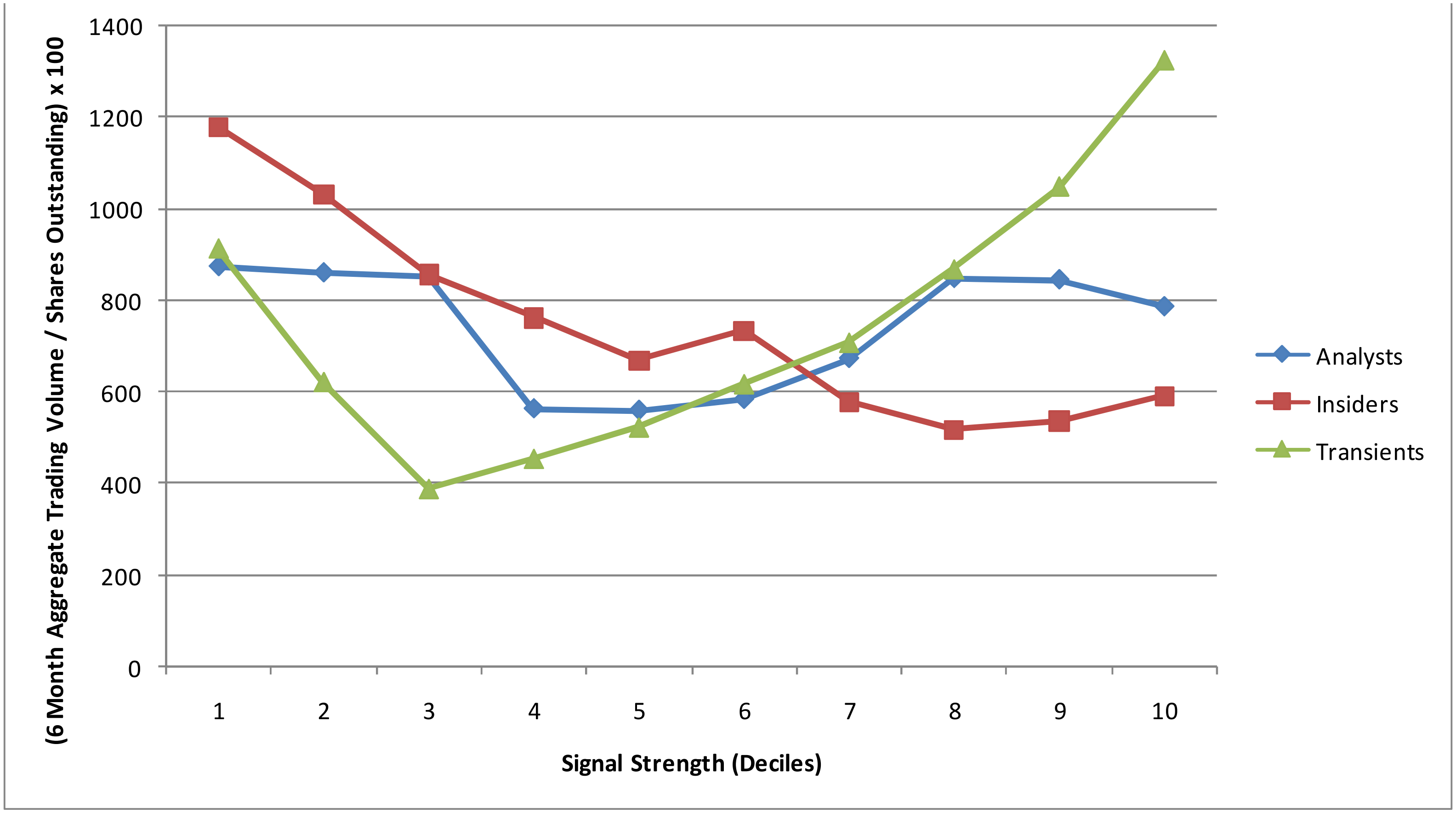
This figure presents average prior 12-month returns from NYSE/NASDAQ/AMEX firms between 1994-2005 across the decile-ranked informed signals of analysts, transient institutions, and analysts, as detailed in Section IV.B. Prior 12-month returns are calculated as monthly compounded raw returns using the Center for Research in Security Prices (CRSP) monthly stock file.

Figure 1. 6 Month Prior Returns vs. Informed Signals



This figure presents market-to-book ratios from NYSE/NASDAQ/AMEX firms between 1994-2005 across the decile-ranked informed signals of analysts, transient institutions, and analysts, as detailed in Section IV.B. Market-to-book ratios are calculated using the Compustat Industrial Quarterly database at the start of each quarter as the market value of equity (product of common shares outstanding multiplied by share price) divided by the book value of equity.

Figure 2. Market to Book vs. Informed Signals



This figure presents trading volume from NYSE/NASDAQ/AMEX firms between 1994-2005 across the decile-ranked informed signals of analysts, transient institutions, and analysts, as detailed in Section IV.B. Trading volume is calculated as the sum of monthly volume for each firm over the prior six months divided by the firm's total number of common shares outstanding at the start of each quarter.

Figure 3. 6-Month Turnover vs. Informed Signals

for liquidity. Their U-shaped plot indicates that the largest levels of net buying/selling occur when past trading volume has been high. Analysts also show U-shaped preferences in their stock recommendation behavior with regards to trading volume. Finally, insiders tend to sell most strongly when volume is high, and buy most strongly when volume is low, perhaps consistent with high-volume firms being correlated with investor overreaction and firm overvaluation (Miller, 1977).

Overall, this analysis is consistent with expectations derived from past literature. Insiders appear to be contrarians who favor low volume, neglected value stocks with poor past returns. Conversely, the behavior of analysts and institutions appears to favor firms with high momentum and high expected growth.

To supplement these univariate analyses, I examine the relative preferences of each informed party for the above firm characteristics within a multivariate framework. Due to the non-linear U-shaped distribution for volume, I divide each signal into two partitions by the median signal value, and designate each half as either a favorable or unfavorable signal for each party depending upon whether that group's signal is above or below the median value. For variables in the unfavorable partitions, I multiply the rank signal by -1, such that the coefficients on the independent variables now proxy for increases in net selling/downgrading behavior. I then run each of the six dependent variables (Analyst Favorable, Analyst Unfavorable, Institution Favorable, Institution Unfavorable, Insider Favorable, Insider Unfavorable) on the predicted variables, while using size as a general control.

Table 2 summarizes these results by showing the coefficients of the key variables in each of the six regressions. The differences between coefficients for momentum, book-to-market, and volume across each group are significant at the 0.01 level.[9] Results of multivariate regressions are consistent with the earlier results. One

[9] Test Statistic is calculated according to Clogg, Petkova and Haritou (1995).

Table 2. Multivariate Analysis of Relative Preferences for Volume, B/M, and Momentum for Informed Parties

$$Signal_t = \alpha + \beta_0 Volume_{t,t-6} + \beta_1 Momentum_{t,t-12} + \beta_2 B/M_t + \beta_3 Size_t + \varepsilon_t$$

PANEL A: FAVORABLE SIGNALS						
	ANA	**TI**	**CI**	**ANA - CI**	**TI - CI**	**TI - ANA**
VOLUME	0.00202***	0.00421***	-0.0003302***	0.002350***	0.004540***	0.002190***
B/M	-0.61698***	-1.54654***	2.01024***	-2.627220***	-3.556780***	-0.929560***
MOMENTUM	0.13486	1.80527***	-2.27198***	2.406840***	4.077250***	1.670410***
SIZE	2.46627***	-0.43121***	-3.19219***	5.65846***	2.76098***	-2.89748***

PANEL B: UNFAVORABLE SIGNALS						
	ANA	**TI**	**CI**	**ANA - CI**	**TI - CI**	**TI - ANA**
VOLUME	0.00009011	0.00532***	0.00192***	-0.001830***	0.003400***	0.005230***
B/M	-0.17249***	0.51121***	-3.23554***	3.063050***	3.746750***	0.683700***
MOMENTUM	0.06366	-1.21541***	1.21882***	-1.155160***	-2.434230***	-1.279070***
SIZE	-2.86346***	0.17009***	-2.9832***	0.11974*	3.15329***	3.03355***

Volume is calculated as the aggregated number of shares traded in the prior six months, divided by the number of shares outstanding at the start of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is calculated as the compounded raw returns using CRSP monthly data over the prior 12 months. Size is taken as the log (Market Value of Equity) at the beginning of each quarter, and is used as a control.

Panel A indicates the regression coefficient for each characteristic when regressed on the party's signal. (Un)Favorable signals are those (below) above the median signal rank, calculated as discussed in Section IVB. In Panel B, the ranked signal is multiplied by -1, such that coefficients on the independent variables now proxy for increases in net selling/downgrading behavior. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors.

interesting phenomenon that emerges from this analysis, however, is that transient institutions appear to act as "ultra-momentum" style investors. Of the three entities, they most strongly prefer buying high volume, high momentum, and glamour stocks. Insiders have buying preferences diametrically opposed to those of institutions. Analogously, the analysis of the "negative" signals shows that institutions are most likely to be net sellers of stocks with the worst past returns, the lowest M/B (ultra-value firms), and the highest levels of volume. Again, insiders' selling preferences are in direct contrast to those of institutions. Of the three groups, the firms that they sell most strongly have the highest levels of M/B (ultra-glamour firms) and highest levels of past returns. Finally, the actions of analysts appear less extreme than those of institutions, falling between the actions of institutions and insiders.

Why is it that institutions appear to have similar, but more extreme, preferences for momentum and glamour, relative to analysts? One possibility lies in their reliance on sell-side analysts' in making their trading decisions. Cheng, Liu, and Qian (2006) note that only 5% of institutions rely exclusively on "buy-side" reports. Rather, the majority use a combination of reports from buy-side (exclusive private information) and sell-side analysts (information available for public consumption), and weight each report depending on its strength and accuracy. In order to do so, institutions must wait for the production, disclosure and assimilation of sell-side reports prior to making their trades. If the weight of the sell-side analyst report is sufficiently large in the institutions' trading decision, then the observed actions of the institutions appear to mimic analysts' actions, after controlling for such delays.[10]

[10] Note that because buy-side analysts' reports are private, an asymmetry in information disclosure exists, and sell-side analysts would be unable to use such information in their stock recommendations in a similar fashion.

Given that the preferred characteristics of analysts and institutions are largely similar, the lag from institutions prior to their trades cause them to appear as "ultra-momentum" investors relative to analysts.

V. Relative Signal Informativeness at Different Horizons: Results

Table 3 reports mean size-adjusted[11,12] buy and hold abnormal returns over three, six, and twelve month time horizons within each decile of signal strength for analysts, institutions, and insiders. Hedge portfolio returns are calculated as the difference between the BUY (highest quintile ranking) and SELL (lowest quintile ranking) portfolios. A summary of these univariate results is as follows: (1) hedge portfolio returns created from insiders' signals are superior to those of analysts' and institutions' at all time horizons. (2) Consistent with prior research, the returns for insiders are driven largely by the BUY portfolio. (3) Confirming predictions in Section III, the magnitudes of the insiders' hedge returns continue to grow with time, earning 2.86% over the first six-months and 4.31% over the second six-months of the 12-month window, while institutions and analysts have the highest magnitude of hedge portfolio returns at the 6 month horizon, with returns becoming insignificantly different from zero at the longest, 12-month, horizon. Overall, the evidence of insider superiority increasing over time is consistent with them being contrarians that buy late-stage losers and are able to extract the full benefits of the momentum cycle over the longest time periods. Evidence of hedge returns for analysts and institutions only being significant at 3 and 6 months is also consistent with their preferences for momentum stocks, and their delayed buying behavior relative to insiders.

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[11] Size Adjusted Buy and Hold Abnormal Returns (BHAR) are created by calculating each firm's monthly abnormal return by subtracting the average return for firms in the same NYSE size decile, then compounding the corresponding abnormal returns over the specified horizon period. If a firm delists, CRSP delisting returns are used, which are calculated by comparing the value after delisting against the price on the security's last trading period.

[12] Similar inferences are obtained when reporting returns with market-adjusted and raw returns.

Table 3. Future Returns by Informed Party Signal Strength

	Panel A: Financial Analysts (ANA)			Panel B: Corporate Insiders (CI)			Panel C: Transient Institutions (TI)		
SIGNAL STRENGTH (Decile)	**3 Month**	**6 Month**	**12 Month**	**3 Month**	**6 Month**	**12 Month**	**3 Month**	**6 Month**	**12 Month**
10	0.014032	0.026531	0.04857	0.025925	0.04612	0.10988	0.012181	0.011606	0.008834
9	0.005762	0.01324	0.028571	0.01593	0.01873	0.05755	0.010084	0.019503	0.025243
8	0.002695	0.0052	0.016674	0.006193	0.0124	0.03423	0.009478	0.021785	0.041443
7	0.005187	0.008093	0.019441	0.009007	0.01545	0.03006	0.004522	0.010178	0.041955
6	0.013115	0.021359	0.054112	0.002071	0.00093	0.00534	0.006353	0.008317	0.031487
5	0.009998	0.013919	0.035932	0.000916	0.00359	0.02169	0.001829	0.00627	0.027916
4	0.009919	0.020065	0.046944	0.002795	0.00109	0.01231	0.002181	0.002158	0.02054
3	0.000846	0.000055	0.011746	-0.001356	0.00308	0.01217	0.001883	0.010192	0.038995
2	-0.000892	-0.003249	0.006342	-0.002288	0.00751	0.0134	0.004604	0.008487	0.031601
1	-0.003183	0.002186	0.034791	-0.001737	0.00013	0.00827	0.005049	0.01124	0.038651
BUY (9-10)	0.009897	0.0198855	0.0385705	0.0209275	0.032425	0.083715	0.0111325	0.0155545	0.0170385
SELL (1-2)	-0.0020375	-0.0005315	0.0205665	-0.0020125	0.00382	0.010835	0.0048265	0.0098635	0.035126
BUY - SELL	*1.19%*	*2.04%***	*1.80%**	*2.29%****	*2.86%****	*7.29%****	*0.63%*	*0.57%*	*-1.81%***

This table documents average future buy and hold size-adjusted returns calculated as described in Barber, Lyon, and Tsai (1999) for each ranked signal, sorted by decile over three, six, and twelve month time horizons. The signals of analysts, transient institutions, and analysts, ANA, TI, and CI, are detailed in Section IV.B. Hedge returns are calculated by subtracting the SELL portfolio from the BUY portfolio returns, where BUY and SELL portfolios correspond to the lowest and highest quintile of signal strength for each group, respectively. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively.

Table 4 compares the predictive power of each party's signal when all three signals are used in tandem. For ease of interpretation, I divide the decile rank of each signal by 9, such that the independent variable for signal strength now ranges between 0 and 1. The coefficient for each party's signal now represents the signal's ability to predict future returns in percentage terms. Following prior literature (Fama and French, 1992), (Jegadeesh et al, 2004) size, book to market, momentum, market beta, and share turnover are used as controls for expected returns. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return, as well as a prior return in months seven through twelve. Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Inferences from the multivariate analyses, after controlling for the aforementioned firm characteristics, yield similar conclusions to those in Table 3. The relative magnitudes of each signal's coefficient confirms the superiority of the insider signal, with the insider advantage being most evident at the twelve month horizon, and institutions being the least predictive at all three time horizons. Consistent with the prior univariate analysis and the momentum-like preferences of analysts and institutions, Table 4 shows that the coefficients on institutions' and is largest at the six month horizon, and insignificant at 12 months, while analysts' ability to predict returns at the 12-month period becomes only marginally significant at the 10% confidence level. The monotonic increase in the insider signal coefficient over time is consistent with their "late-stage" contrarian behavior.

Table 4. Regressions of Future Returns on Informed Signals

	Panel A: 3 Month Size-Adjusted Future Returns		Panel B: 6 Month Size-Adjusted Future Returns		Panel C: 12 Month Size-Adjusted Future Returns	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
INTERCEPT	0.009372	1.68*	0.033576	3.37***	0.10388	5.39***
ANA	**0.010538**	**3.3*****	**0.015233**	**3.2*****	**0.01676**	**1.83***
CI	**0.021547**	**5.63*****	**0.0274**	**4.25*****	**0.049543**	**4.04*****
TI	**0.010264**	**2.98*****	**0.010374**	**1.93***	**0.003527**	**0.38**
BEME	0.012021	5.86***	-0.00529	-4.35***	-0.0143	-5.42***
SIZE	-0.00263	-4.03***	0.017687	4.79***	0.020664	2.71***
MOM6RET	0.02572	5.71***	0.00323	1.12	0.015216	2.35**
MOM7RET12	-0.00633	-1.74*	-0.00071	-2.53**	-0.00146	-3.05***
TURN	-0.0003	-1.67*	0.055811	6.63***	0.030996	2.35***
BETA	0.003554	2.05**	-0.01821	-2.87***	-0.0329	-3.45***

This table reports regressions of future market size-adjusted buy-and-hold abnormal returns on all three signals. Size-adjusted buy-and-hold abnormal returns are calculated as described in Barber, Lyon, and Tsai (1999). Size, book-to-market, momentum, CAPM beta, and share turnover are used as controls for expected returns. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors.

Table 5 presents results regarding the relative informativeness of each party's signal under conditions of inter-party disagreement. For each party, I code signals into two partitions of BUY and SELL signals, based upon whether their signal rank is above or below the median. These signals are then used to create the disagreement portfolios. I measure the informativeness of each party's signal by examining the differences in means of size-adjusted BHAR's for each disagreement portfolio versus a control group where a full consensus exists. For example, I measure the incremental informativeness of an insider BUY signal as the hedge portfolio where insiders are issuing BUY signals, and analysts and institutions are issuing SELL signals, less the consensus control portfolio where all three groups are issuing BUY signals. Given that the consensus buy yields the largest BHAR's over all three periods, the strongest deviating buy signals will have the smallest negative values when the consensus BUY is subtracted from the deviating BUY signal. Similarly, after subtracting the consensus SELL from the disagreeing SELL, the strongest SELL signal will have the smallest positive values. Figure 4 illustrates these ideas graphically for disagreeing BUY signals at a given time horizon.

Table 5 shows the insider/buy/12-month deviations to be the most informative signal. Size-adjusted BHAR's from this portfolio earn 4.38%, which is statistically identical to a full-consensus buy signal, i.e. the difference between the disagreeing insider/buy and the consensus buy is 0.00%. Similarly, analyst/buy and institution/buy deviations are most informative at the 3 month horizon, exhibiting -1.87% and -1.95% less than a consensus buy, respectively. The degree of informativeness for both analysts/buy and institutions/buy markedly decreases at longer horizons. The returns of disagreeing analysts/buy signals relative to a full consensus are -2.89% and -2.35%

Table 5. Hedge Portfolio Returns of Informed Signals Under Inter-Party Disagreement

Panel	Group	Return Horizon	Size-Adjusted Future Returns	t-stat	Lesser Return of Disagreeing BUY vs Consensus BUY	t-stat
	Consensus BUY	3 Month	1.75%	5.59***		
		6 Month	3.19%	6.20***		
		12 Month	4.38%	5.24***		
PANEL A: DEVIATING BUY SIGNALS	CI	3 Month	0.64%	2.67***	-1.11%	-2.85***
		6 Month	1.06%	2.64***	-2.13%	-3.31***
		12 Month	4.38%	5.04***	0.00%	0.00
	ANA	3 Month	-0.13%	-0.42	-1.87%	-4.32***
		6 Month	0.31%	0.72	-2.89%	-4.28***
		12 Month	2.03%	2.95***	-2.35%	-2.16**
	TI	3 Month	-0.20%	-0.73	-1.95%	-4.70***
		6 Month	-0.37%	-0.91	-3.56%	-5.50***
		12 Month	0.53%	0.84	-3.86%	-3.74***
		Return Horizon	**Size-Adjusted Future Returns**	**t-stat**	**Lesser Return of Disagreeing SELL vs. Consensus SELL**	**t-stat**
	Consensus SELL	3 Month	-0.62%	-2.52**		
		6 Month	-0.04%	-0.09		
		12 Month	0.54%	0.87		
PANEL B: DEVIATING SELL SIGNALS	CI	3 Month	0.63%	2.23**	1.24%	3.18***
		6 Month	1.18%	2.77***	1.22%	2.02**
		12 Month	2.21%	2.97***	1.67%	1.64
	ANA	3 Month	1.58%	4.60***	2.19%	5.25***
		6 Month	2.29%	4.67***	2.33%	3.71***
		12 Month	5.73%	6.35***	5.19%	4.78***
	TI	3 Month	1.07%	3.92***	1.69%	4.53***
		6 Month	1.49%	3.62***	1.52%	2.65***
		12 Month	4.85%	5.50***	4.31%	3.87***

This table reports hedge portfolio returns using the means of size-adjusted buy-and-hold abnormal returns, calculated as described in Barber, Lyon, and Tsai (1999), over three, six, and twelve month horizons when one group's action deviates from the actions of the other two. In Panel A, the deviating party has a BUY signal, where the other two parties issue SELL signals within the same quarter. In Panel B, the deviating party has a SELL signal, where the other two party members issue BUY signals within the same quarter. BUY (SELL) signals are those that fall into the highest (lowest) quintile of signal ranks for each informed party within the given period. Hedge portfolio returns for each group are calculated in panel A (B) as the difference between deviating signal portfolios and the full-consensus SELL (BUY) portfolios. Statistical significances at 1%, 5%, and 10% are reported as ***, **, and *, respectively.

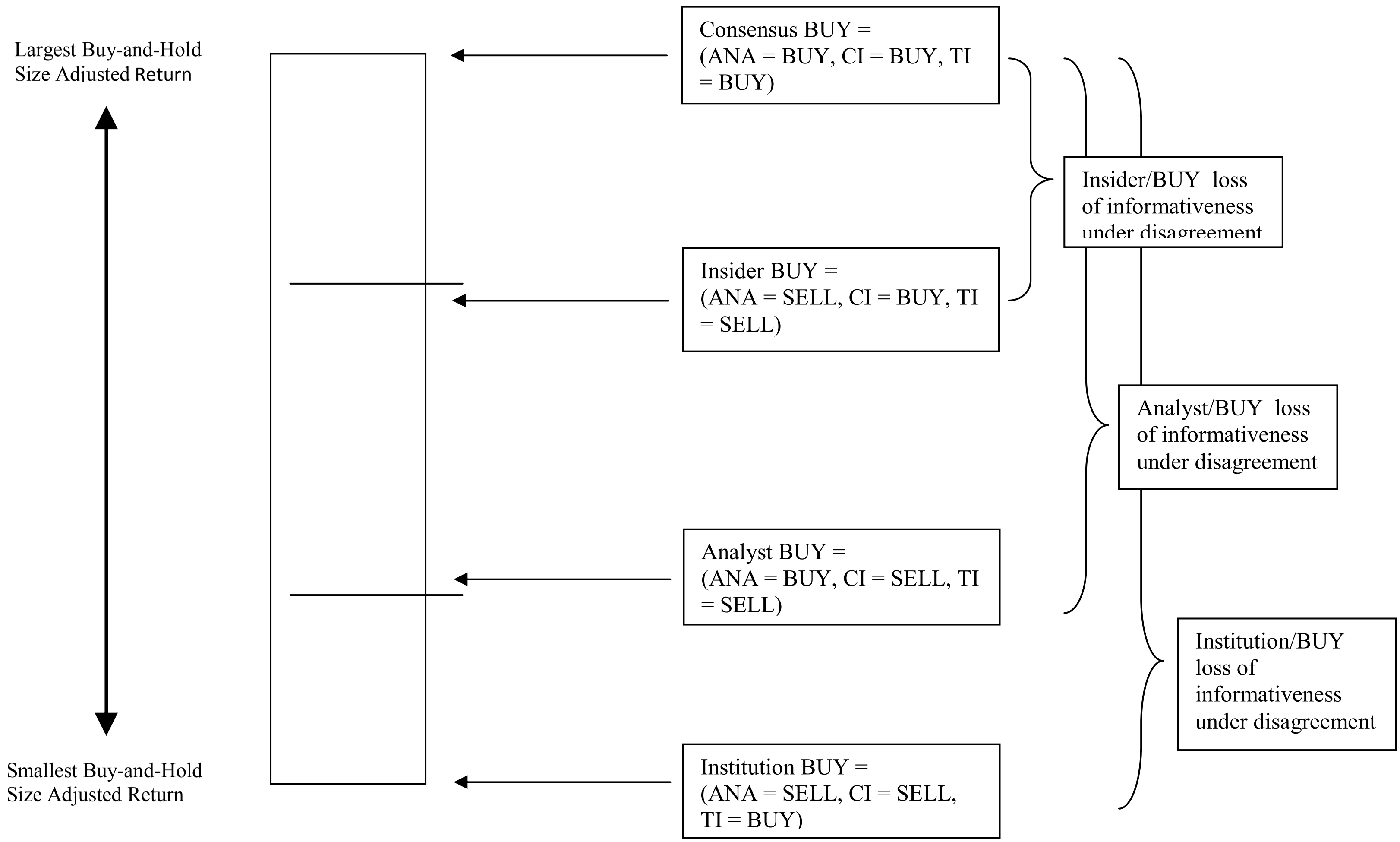

Figure 4. Measuring Incremental Informativeness under Disagreement at a Given Time Horizon

at 6 and 12 months, respectively, while the returns of disagreeing institutions/buy signals relative to a unanimous buy signal are -3.56% and –3.86% at 6 and 12 months, respectively. These results may be attributable to the fact that transient institutions and analysts prefer late-stage winners, leaving them closest to an impending reversal, and thus making them less informative even at mid-stage horizons. Insider/buy deviations at the 3 and 6 month horizons remain most informative when compared to their counterparts, confirming the dominance of the insider buy signal over the combined sell signals from analysts/institutions even at the momentum traders' preferred horizons.

With regards to sell signals under conditions of disagreement, insiders' had the most informative signal at all three horizons when compared to their collective counterparts. The difference between sell-signal disagreement strength across parties is strongest at the 12 month horizon. At this horizon, insider signals earn 1.67% less than a consensus sell signal, while analyst and institution signals earn 5.19% and 4.31% less than a consensus sell signal, respectively. With respect to analysts' and institutions', both groups performed most poorly at the 12-month horizons, again consistent with prior predictions that fighting against the insider buy at the 12-month horizon would lead to a weak signal.

The overarching theme from this analysis of inter-party disagreement is that the ability to deviate and remain predictive of future returns relies on two factors: (1) the strength of the deviating signal over the particular time horizon, and (2) the relative weakness of the countervailing forces. The insider signal is dominant under all time horizons, and most dominant when buying and returns are calculated over a 12-month time horizon. Other parties actions' have greater informativeness when insiders' countervailing actions are mitigated because they are selling, or because returns are being predicted over shorter time horizons.

VI. Factors Influencing the Hierarchy of Informativeness

Results in the preceding section confirm the superiority of the insider signal, followed by analysts and institutions. The following subsections investigate the impact of various firm and industry-specific factors on the relative hierarchy of signal informativeness. In general, I argue that each of these parties has a relative advantage with respect to a particular type of information, and attempt to show that when such information has already been impounded into prices, the actions of these groups become significantly weakened in predicting future returns. Because prior literature has shown institutional investors to take advantage of private communications with insiders, while also using analysts' opinions in making their trading decisions, it remains ambiguous whether institutions have a relative advantage about a particular source of information. Therefore, I make no hypotheses regarding how the variables for price informativeness will affect transient institutions' signals, and focus my analyses primarily on the hierarchy between analysts and insiders.[13]

VI.A. Predicted Effects of Firm-Specific Price Informativeness on Insiders' Predictive Ability

Piotroski and Roulstone (2005) show that insiders' trades reflect their privileged knowledge of future firm-specific information, in the form of future cash flows and earnings. Assuming that the insiders' dominant signal in predicting future returns, as shown in Section V, is driven by firm-specific information, then the implicit assumption underlying the hierarchy between these informed agents is that

[13] Despite the lack of direct hypotheses for institutions, in untabulated analyses, I run regressions with identical form to those found in section VI, with the institutional signal as an additional control variable. Results related to both economic significance and statistical validity remain unchanged.

firm-specific information, in general, is more responsible for driving stock prices than industry or common, macro-level information. In this section, I use two different proxies for the informational environment to examine how the relative hierarchy between insiders and analysts is affected when a firm's stock price differs by the degree to which it is reflective of firm-specific information.

In general, I argue that because the strength of the insider signal is more likely to rely on firm-specific information, the insider' signal will be mitigated if the firm's stock price is already reflective of such firm-specific information. Conversely, since analysts depend largely on industry and macro-level information in signaling their opinions to the market, their signals will be less affected under these conditions.

The two measures of price informativeness used in my subsequent analyses are the probability of informed trade (PIN) and future earnings response coefficient (FERC). I briefly detail each variable prior to discussing how the informed signals' will be expected to differ across the various information regimes.

VI.A.1. Probability of Informed Trade (PIN)

The PIN variable was developed by Easley, Kiefer, and O'Hara (EKO, 1997) within a microstructure trade model to measure the probability that a given trade is driven by private information, and has since been used in other studies as a proxy for information asymmetry (Brown, Hillegeist, and Lo, 2004; Brown and Hillegeist, 2007) . The model can be summarized as follows: Over a trading day, prices converge to their full information levels as private information is fully revealed through the trades of informed traders, thus the market maker is able to draw inferences about the presence of private information based on the observed order flow imbalance. PIN is calculated as follows:

$$PIN = \alpha\mu / (\alpha\mu + \varepsilon_s + \varepsilon_b),$$

where α is the probability of a private information event at the start of the trading day, μ is the arrival rate of orders motivated by private information, and ε_s and ε_b is the arrival rate of orders from uninformed sellers and buyers, respectively. Thus, the numerator equals the number of trades based on private information, while the denominator proxies for the total number of trades from both informed and uninformed investors. Intuitively, the ratio then calculates the probability that the trade is based on private information.

Thus, assuming PIN is an effective proxy for information asymmetry, I predict that the insider signal will be significantly less predictive of future returns when PIN is low. In addition, since analysts appear to form their signals from common, public information, I expect the strength of their signals to be relatively unaffected by the PIN variable.

I use quarterly estimated PIN data of the EKO model, graciously provided by Stephen Brown, from 1994-2006. These PIN estimations cover stocks in the NYSE, AMEX, and NASDAQ markets, and require a minimum number of 30 active trading days within a given quarter to provide a reliable estimate. I remove all corner solutions inherent in the computation of PIN from my sample, as these estimates are likely to be unreliable results from the optimization process. I create a dummy-variable with the PIN data from the prior quarter of each firm, assigning the subset of firms with the lowest levels of PIN with a value of one, and a value of zero to the remainder of the firm-years.[14]

[14] For robustness, I also estimate PIN using an average of each firm's PIN in the trailing 12 months. Results occur without any major changes in statistical inference, and are available upon request.

VI.A.2. Future Earnings Response Coefficient (FERC)

FERC is a measure of stock price informativeness that was developed by Collins, Kothari, Shanken, and Sloan (1994). This approach measures the amount of future earnings information that has already been impounded into current stock prices by examining the degree to which future earnings load on regressions of yearly stock returns, after controlling for the firm's past and present levels of earnings, and the firm's future returns. If the coefficient on future earnings is high, then prices are more informative of future earnings.

The structural models used in computing FERC follow Lundholm and Myers (2002), who modify the original CKSS specification by aggregating the future earnings to create a more powerful test, as follows:

$$R_{it} = a + b_o X_{it-1} + b_1 X_{it} + b_2(X_{it+1} + X_{it+2} + X_{it+3}) + b_3 R_{it+3} + \varepsilon_{it}$$

X_{it+k} is the annual earnings per share , while R_{it} is a firm's annual return beginning at time t, and R_{it+3} is a three year future return for the firm. R_{it+3} is used to control for an errors-in-variables problem involved in using realized earnings as expected earnings. b_2 is the future earnings response coefficient. If b_2 is high, then stock returns are more strongly informative of future earnings.

FERC has been used within a number of disclosure papers as a proxy for stock price informativeness of future earnings. In general, the literature shows that firms with higher quality or more frequent disclosures have informational environments that are more revealing of firm-specific information, thereby resulting in higher FERC values. Gelb and Zarowin (2002) and Lundholm and Myers (2002) both document this linkage by showing that firm's with higher AIMR-FAF annual disclosure ratings have stock prices that are more informative of firm-specific information, as measured by higher FERC values. Tucker and Zarowin (2006) document a positive relationship between income smoothing and FERC, and conclude that income smoothing increases the revelation of future earnings in current returns. Choi et al. (2008) find a positive association between FERC and the frequency and precision of management forecasts, while Orpurt and Zang (2009) measure FERC in order to show that the direct method of cash-flow disclosures increases stock price informativeness over firms that derive their cash flow statements using the indirect method. My use of the future earnings response coefficient differs from that of previous literature. While prior research measures changes in FERC as the dependent variable, I use FERC as an independent variable proxying for the firm-specific informational environment and then measure the difference in the two informed parties' signals in predicting future returns.

Assuming that FERC is an effective proxy for the degree to which future firm-specific information is impounded into stock prices, my predictions for the impact of FERC on analysts' and insiders' signals are opposite to the prior PIN predictions. Specifically, when FERC is high, I predict that the insiders' advantage of future firm-specific information will be less useful as such information is already impounded into stock prices, thereby leading to an attenuation of the insider signal. Extracting from prior literature, since the analysts' advantage appears to be derived from intra-industry information, I expect the analysts' signal to be less attenuated relative to the insiders' signal.

I estimate the future earnings response coefficients with yearly Compustat and CRSP monthly stock files. Following Tucker and Zarowin (2006), I scale all EPS variables by the stock price at the beginning of the fiscal year, and truncate the highest and lowest 1% of the distribution across the entire domain of independent variables. I then run rolling panel regressions for the trailing 36-months[15] of data across each

[15] In untabulated sensitivity tests, I also run the FERC analysis using rolling regressions of the prior 48 and 60 months, and also change the number of years of aggregated future earnings to 4 and 5 years. Results of such analyses are statistically similar, and hence, unreported.

industry, as specified by SIC two-digit industry code.[16] To remain consistent in my analyses, I create a dummy variable equal to one for the top quintile of industry-years for b_2 (the future-earnings response coefficient), and equal to zero for the remaining firms.

VI.B. Results of Firm-Specific Price Informativeness Analyses

I analyze the effects of both proxies for the informational environment on the analysts' and insiders' signals by running the following panel data regressions using 3, 6, and 12-month future size adjusted returns (SAR) as the dependent variables. The specification contains interactions for price informativeness, as shown below:

$$SAR_{itn} = a + b_1ANA_{it} + b_2ANA_{it}{*}INFO_{it} + b_3CI_{it} + b_4CI_{it}{*}INFO_{it} + b_5INFO_{it} + b_6BEME_{i,t} + b_7SIZE_{it} + b_8MOM6RET_{it} + b_9MOM7RET12_{it} + b_{10}TURN_{it} + b_{11}BETA_{it} + \varepsilon_{it}$$

Control variables for firm-characteristics remain the same as those in the prior analyses. SAR_{itn}, where n= {3,6,12} denotes future returns over a 3, 6, or 12 month time window. As previously discussed, INFO is a dummy with a value of 1 for firms with *the lowest-quintile of PIN's* within the prior quarter in the first set of analyses, and for firms in *the highest-quintile of FERC's* compiled over a 36 month rolling regression in the second set of analyses. Thus, in both cases, the coefficients on interaction variables for the PIN and FERC dummies with the insider signal is expected to be negative, while the coefficients of interaction variables for the PIN and FERC dummies with the analysts' signal is expected to be insignificant and less negative when compared to that of the insiders' coefficient.

[16] FERC can also be estimated on a firm-by-firm basis. While these results (not reported) have similar inferences, estimating FERC by SIC code allows me to keep a larger number of firm-quarters, hence increasing the statistical power of the analyses.

Results of analysis from the preceding equation are shown in Table 6 and Table 7. Overall, both sets of results confirm the predictions of the differential effects of PIN and FERC on the analyst's and insider's signals. As conjectured for firms with the lowest levels of PIN, the insider signal is significantly attenuated at the 3, 6, and 12 month return intervals, earning 2.3%, 2.9%, 7.4% less than firms where PIN is not in the lowest quintile. Conversely, the analyst signal is only significantly weakened at the three-month horizon, at -1.6%. Across all three horizons, firms with the lowest levels of PIN weaken the power of the insiders' signal more than that of the analysts' signal.

In the FERC analysis, the magnitude to which the insiders' signal is diminished is significantly negative at -3.7%, -7.1%, and -8.3% for 3, 6, and 12 month horizons, respectively, while the coefficient of ANA*FERC is only marginally negative at the 6 month horizon (p=0.08), and insignificantly negative at 3 and 12 months. Summing the coefficients on CI + CI*FERC to show the magnitude of the insiders' signal when FERC is high reveals their predictive ability to be insignificantly different from zero at all three time horizons. Evidence from both sets of analyses supports two overarching themes. First, insiders' appear to be largely reliant on their firm-specific informational advantages in predicting future returns. Under environments where stock prices appear to be efficient with respect to the pricing of future

Table 6. Regressions of Size-Adjusted Future Returns on Informed Signals and Probability of Informed Trade (PIN)

	Panel A: 3 Month Size-Adjusted Future Returns		Panel B: 6 Month Size-Adjusted Future Returns		Panel C: 12 Month Size-Adjusted Future Returns	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Intercept	0.011946	1.92*	0.045605	4.14***	0.115474	5.57***
ANA	0.016649	3.83***	0.017554	2.68***	0.011628	0.87
ANA*PIN	**-0.01624**	**-2.54****	**-0.00777**	**-0.8**	**0.010262**	**0.58**
CI	0.027124	5.82***	0.035707	4.52***	0.071736	4.72***
CI*PIN	**-0.02169**	**-2.84*****	**-0.02905**	**-2.4****	**-0.07348**	**-3.48*****
PIN	0.023786	4.32***	0.031411	3.74***	0.053362	3.43***
BEME	-0.0035	-4.24***	-0.00781	-5.11***	-0.01815	-5.57***
SIZE	0.012826	6.19***	0.018301	4.86***	0.021353	2.77***
MOM6RET	-0.00034	-1.76*	-0.00095	-3.23***	-0.00197	-3.84***
MOM7RET12	0.029761	6.46***	0.061302	7.1***	0.036101	2.61**
TURN	-0.00505	-1.36	-0.0144	-2.16**	-0.02989	-2.98***
BETA	0.004562	2.49**	0.004526	1.49	0.018246	2.66***

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section IV.B and firm-specific probabilities of informed trade (PIN). Panels A, B, and C report future SAR's at the 3, 6, and 12 month horizons. PIN calculations, courtesy of Stephen Brown, are further detailed in Section VI.B and calculated according to the methodology derived by Easley, Kiefer, and O'Hara (1997). PIN is then converted into a binary variable where firms in the lower quintile are assigned a value of one, while all remaining firms are assigned a value of zero. Size, book-to-market, momentum, CAPM beta, and share turnover are used as controls for expected returns. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors.

Table 7. Regressions of Size-Adjusted Future Returns on Informed Signals and Future Earnings Response Coefficient (FERC)

	Panel A: 3 Month Size-Adjusted Future Returns		Panel B: 6 Month Size-Adjusted Future Returns		Panel C: 12 Month Size-Adjusted Future Returns	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Intercept	0.018933	2.57**	0.046809	3.71***	0.133044	5.42***
ANA	0.010923	2.19**	0.021287	2.82***	0.011599	0.76
ANA*FERC	**-0.00229**	**-0.2**	**-0.03266**	**-1.85***	**-0.04672**	**-1.54**
CI	0.030098	5.25***	0.045045	4.8***	0.078523	4.24***
CI*FERC	**-0.04756**	**-3.81*****	**-0.08204**	**-3.99*****	**-0.09015**	**-2.44****
FERC	0.007015	0.73	0.022859	1.44	0.016889	0.65
BEME	-0.0034	-3.74***	-0.00697	-4.25***	-0.01961	-5.4***
SIZE	0.012705	4.42***	0.017995	3.59***	0.01825	1.77*
MOM6RET	-0.00027	-0.9	-0.00088	-1.83*	-0.00231	-2.72***
MOM7RET12	0.026815	5.25***	0.054602	5.96***	0.033048	2.09**
TURN	0.00189	0.38	-0.00604	-0.71	-0.0236	-1.85*
BETA	0.000759	0.27	-0.00166	-0.38	0.021745	2.1**

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section IV.B and future earnings response coefficients (FERC). Panels A, B, and C report future SAR's at the 3,6, and 12 month horizons. FERC, further detailed in Section VI.B, is calculated using a rolling regression over the past 36 months for each firm in a manner similar to that of Lundholm and Myers (2002). FERC is then converted into a binary variable where firms in the upper quintile are assigned a value of one, while all remaining firms are assigned a value of zero. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors.

earnings, or when incoming flows of private information are infrequent, the insider signal—while most robust in the unconditional analyses, becomes unable to predict future abnormal returns. Second, the analysts' signal appears to be unimpacted by these partitions for firm-specific informational efficiency, implying that the predictive ability of their aggregate actions is derived elsewhere. In the following section, I test the level to which analysts' signals rely on industry-level informational efficiency in predicting future returns.

VI.C. Predicted Effects of Industry Information Diffusion Rates on Analysts' Predictive Ability

As previously discussed in Section II, analysts are generally assigned to cover a specific group of firms that operate within a given sector or industry, thereby allowing them to develop an expert knowledge of the valuation inputs for their assigned firms. Piotroski and Roulstone (2004) show that the stock recommendations of analysts impound industry and market level information into stock prices, as measured by firm-level synchronicity. In this section, I examine how the predictive ability of analysts is affected by the efficiency at which a firm assimilates industry-level information into prices. In particular, I argue that when a firm's stock price is more delayed with respect to the absorption of industry-level information, prices become less reflective of future cash flows related to industry dynamics. Given previous discussions regarding the analyst expertise of industry-specific information, when the speed of information diffusion into prices is slower, the magnitude of industry-level information impounded into prices is lower, thereby making the aggregate actions of analysts more value-relevant, and resulting in their signals being more predictive of future stock returns. Conversely, with no priors regarding industry-specific expertise for insiders, the magnitude of the insider signal should remain unchanged across changes in industry diffusion rates.

Hou (2007) examines the speed of industry information diffusion amongst firms, and finds that firms with higher-levels of industry delay tend to be characterized as smaller firms with higher levels of analyst dispersion, lower levels of trading volume, and lower levels of market share within their given industry. Hou notes that while slow information diffusion could be caused by a firm's neglected information environment, it could also result from other sources, such as noise traders, limited investor attention or processing power, short-sell constraints, microstructure frictions, and other institutional constraints. I construct a variable that measures the degree of market-efficiency for industry-level information in a manner similar to Hou and Moskowitz (2005), using the following equation:

$$\begin{aligned} FirmRET_{it} = {} & a + b_1\,MktRET_{jt} + b_2\,MktRET_{jt-1} + b_3\,MktRET_{jt-2} + b_4\,IndRET_{kt} \\ & + b_5\,IndRET_{kt-1} + b_6\,IndRET_{kt-2} + \varepsilon_{it} \end{aligned}$$

VI.D. Results of Industry Information Diffusion Analyses

Using the aforementioned equation, I run firm-by-firm rolling regressions over the prior 36 months for each company's monthly raw return on the CRSP value-weighted return, the SIC two digit industry-return, and the two monthly lags for both the market and industry returns. The sum of the two lagged industry coefficients represents the level of industry delay for each firm. Similar to section VI.B., I assign a value of 1 (high levels of IDELAY) for the quintile of firms with the highest value of the summed coefficients, and assign a value of 0 to the remaining firms. I run the following specification for 3, 6, and 12 month future size-adjusted returns:

$$SAR_{itn} = a + b_1ANA_{it} + b_2ANA_{it}*IDELAY_{it} + b_3CI_{it} + b_4 CI_{it}*IDELAY_{it} + b_5IDELAY_{it} + b_6BEME_{it} + b_7SIZE_{it} + b_8MOM6RET_{it} + b_9MOM7RET12_{it} + b_{10}TURN_t + b_{11}BETA_{it} + \varepsilon_{it}$$

By construction, higher magnitudes of IDELAY signify that stock prices have slower absorption rates when responding to changing industry dynamics. In these cases, the analysts' reports should contain more value-relevant information. Thus, as previously mentioned, the analysts' signal should be significantly more predictive of future returns when IDELAY is high, compared to their signals when prices are more efficient with regards to industry information, i.e. when IDELAY is low. Conversely, because insiders are specialized in firm-specific information and are not considered to be experts at analyzing industry and macro-level information, the magnitude of their predictive ability should remain unchanged by the IDELAY variable.

Table 8 shows the results for the industry delay analyses. Regressions confirm prior conjectures. When IDELAY is low, the magnitude of the coefficient for the analysts' signal is only marginally significant, earning 0.6%, 0.9%, and 0.9% size-adjusted returns over the 3, 6, and 12 month horizons, respectively. However, in the upper quintile of firms where industry information is delayed, the analysts' signals increase to 3.8%, 5.0%, and 6.4%, and are statistically significant at all of the tested horizons. Results are consistent with the supposition that the industry expertise of sell-side financial analysts drives the predictive ability of their signals, and that their signals are enhanced under conditions where market prices are inefficient with respect to the industry-level information. Regarding insiders, their signal remains strongly predictive of future returns when IDELAY is low, with magnitudes similar to those of the unconditional analyses (Table 4), and is not significantly changed when IDELAY is high. Overall, the combination of the results of Table 8 with the prior analyses in

Table 8. Regressions of Size-Adjusted Future Returns on Informed Signals and Industry Delay (IDELAY)

	Panel A: 3 Month Size-Adjusted Future Returns		Panel B: 6 Month Size-Adjusted Future Returns		Panel C: 12 Month Size-Adjusted Future Returns	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Intercept	0.01684	3.09***	0.040004	4.27***	0.10657	5.90***
ANA	0.006462	1.96*	0.009053	1.86*	0.008241	0.85
ANA*IDELAY	**0.033277**	**3.21*** **	**0.044558**	**2.56** **	**0.061381**	**2.08** **
CI	0.019986	4.98***	0.025391	4.02***	0.04797	4.12***
CI*IDELAY	**0.006658**	**0.63**	**0.003939**	**0.21**	**0.00503**	**0.13**
IDELAY	-0.02204	-2.67***	-0.01797	-1.27	-0.0196	-0.82
BEME	-0.00263	-3.98***	-0.00493	-4.22***	-0.01371	-5.43***
SIZE	0.012292	5.99***	0.018546	5.18***	0.021659	3
MOM6RET	-0.00023	-1.25	-0.00065	-2.44**	-0.00147	-3.24***
MOM7RET12	0.026379	5.91***	0.056503	6.82***	0.030881	2.38**
TURN	-0.00594	-1.64	-0.01833	-2.94***	-0.03358	-3.63***
BETA	0.00393	2.24**	0.003102	1.13	0.014804	2.4**

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section IV.B and industry delay (IDELAY). Panels A, B, and C report future SAR's at the 3, 6, and 12 month horizons. IDELAY, further detailed in Section VI.C, is calculated using a rolling regression over the past 36 months for each firm in a manner similar to that of Hou and Moskowitz (2005). IDELAY is then converted into a binary variable where firms in the upper quintile are assigned a value of one, while all remaining firms are assigned a value of zero. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors.

Section VI.B remains consistent with the premise that the insider dominance in predicting future stock prices originates from knowledge of idiosyncratic information, while analyst predictive ability appears to be derived primarily from industry-level information.

VI.E. Predicted Effects of Firm-Level Synchronicity on the Insider-Analyst Signal Hierarchy

The overall landscape that emerges from the results discussed in Sections VI.B and VI.D illustrates the reliance of the insider' signal on firm-specific information, and the analyst' signal on common, industry-level information in predicting future abnormal returns. In a final set of analyses, I test how the relative hierarchy between analysts and insiders is dependent upon the synchronicity of a firm's stock prices. Synchronicity, calculated as the R-squared of market/industry model asset pricing regressions for a given firm, has been used in prior literature as a measure of whether stock prices are efficient with respect to firm-specific or market and industry information (Durnev et al., 2003; Durnev et al., 2004), as well as common-information (Chan and Hameed, 2006). In these papers, low R-squared's are indicative of a company where firm-specific information has been impounded more heavily into stock prices, whereas high R-squared's are indicative of a firm where common information has been impounded more strongly into stock prices. Therefore, while proxies in prior tests only reflected the efficiency of one specific type of information, synchronicity reflects relative levels of efficiency for firm-specific versus market and industry information, making it a unique setting to test the signal hierarchy between analysts and insiders.

When synchronicity is high, the firm's returns are largely explained with industry and market returns, implying that the firm's environment is more reflective of systematic information than firm-specific information. Since insiders are most advantaged with regards to firm specific information, I predict that the insider signal will be more powerful when synchronicity is higher. In addition, since the value-relevant information produced by analysts has already been reflected in prices when synchronicity is high, I expect that their signal will be relatively weakened when compared to conditions of lower synchronicity. It is interesting to note that these synchronicity analyses result in hypotheses that predict opposite signs on the interactions of ANA and CI with SYNCH, where as other previous analyses predicted significance in one group's interaction, but non-significance in the other group's interaction with the different proxies for informational advantage.

VI. F. Results of Firm-Level Synchronicity Analyses

Remaining consistent with prior methodology in Section VI, I calculate the relative amount of industry and macro-level versus firm-specific information already impounded in prices at any given point by measuring firm-level synchronicity over the preceding 36 months via firm-specific rolling regressions, following the methodology used by Piotroski and Roulstone (2004).[17] Specifically, I calculate synchronicity using the following equation:

$$\text{FirmRET}_{it} = a + b_1\,\text{MaRET}_{jt} + b_2\,\text{MaRET}_{jt-1} + c_1\text{IndRET}_{kt} + c_2\,\text{IndRET}_{kt-1} + \varepsilon_{it}$$

[17] Piotroski and Roulstone show that analysts (insiders) tend to impound more macro-level (firm-specific) information into prices. Other synchronicity determinants include the overall level of firm diversification, the level of intra-industry competition, and the volatility of the firm's earnings stream.

FirmRET is the monthly raw return of the firm, while MaRET is the value-weighted market adjusted return from the CRSP monthly stock file. IndRET is the industry return, and is calculated as the value weighted monthly average for all the firms within a given 2-digit SIC code. Synchronicity is measured as the R-squared of the regression. I rank the synchronicity scores into quintiles, and create a binary variable with a value of 1 for firms in the upper quintile, and a value of zero for all of the remaining firms in the sample. I then run the same set of regression analyses as in the prior tests, using SYNCH as the interaction variable.

Table 9 generally confirms the differing informational advantages of insiders and analysts in each subsample, and illustrates how synchronicity, as a proxy for the existing information environments, can sway the magnitudes of each entity's predictive power in opposing directions. When synchronicity is high, the interaction on SYNCH and the insider signal is directionally positive at the 3 and 6 month horizons, and significantly positive at 12 months. For analysts, the interaction on SYNCH and the analysts signal is significantly negative at the 3 month horizon, and directionally negative at 6 and 12 months. At the 3-month horizon, the interaction coefficient on ANA*SYNCH is significant, negative and larger in magnitude than on the main effect. Thus, when synchronicity is high, these results indicate a complete loss of predictive power for analysts, even at their preferred horizon. At the 12-month horizon, the insider signal earns abnormal returns of 11.5% when synchronicity is high, an increase in signal strength of 7.7% when compared to lower synchronicity firms. Given that prior literature has considered synchronicity to be a noisy signal, i.e. the residual in the asset pricing model could proxy for noise as well as firm-specific information (Teoh et al, 2008), (Ashbaugh-Skaife, et al 2006), it is not surprising to see the interaction coefficient for both parties to only be significant at each parties' preferred horizon. Overall, the results from the synchronicity analysis add further

Table 9. Regressions of Size-Adjusted Future Returns on Informed Signals and Firm-Level Synchronicity (SYNCH)

	Panel A: 3 Month Size-Adjusted Future Returns		Panel B: 6 Month Size-Adjusted Future Returns		Panel C: 12 Month Size-Adjusted Future Returns	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Intercept	0.012394	2.22**	0.039938	4.06***	0.113355	5.94***
ANA	0.016849	4.85***	0.018509	3.47***	0.026536	2.59***
ANA*SYNCH	**-0.02572**	**-3.23*** **	**-0.01598**	**-1.39**	**-0.04069**	**-1.9***
CI	0.018902	4.72***	0.021946	3.13***	0.033061	2.51**
CI*SYNCH	**0.010537**	**1.12**	**0.021938**	**1.48**	**0.076913**	**2.42*** **
SYNCH	0.008929	1.44	0.000721	0.07	-0.00145	-0.08
BEME	-0.00278	-4.05***	-0.00557	-4.43***	-0.01542	-5.7***
SIZE	0.012384	6.05***	0.018102	4.88***	0.019632	2.62**
MOM6RET	-0.00021	-1.19	-0.00062	-2.22**	-0.00139	-2.91***
MOM7RET12	0.028771	6.50***	0.059061	7.15***	0.0328	2.51**
TURN	-0.00535	-1.48	-0.01687	-2.66***	-0.03185	-3.35***
BETA	0.003614	2.03**	0.003229	1.07	0.013138	1.98**

This table reports results of regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA) and corporate insiders (CI) as developed in Section IV.B and firm-level synchronicity. Panels A, B, and C report future SAR's at the 3, 6, and 12 month horizons. Synchronicity (SYNCH), detailed in Section VI.D, is calculated using a rolling regression over the past 36 months for each firm in a manner similar to that of Piotroski and Roulstone (2004). SYNCH is then converted into a binary variable where firms in the upper quintile are assigned a value of one, while all remaining firms are assigned a value of zero. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors.

Table 10. Regressions of Size-Adjusted Future Returns on Informed Signals and Regulation Fair Disclosure (FD)

	Panel A: 3 Month Size-Adjusted Future Returns		Panel B: 6 Month Size-Adjusted Future Returns		Panel C: 12 Month Size-Adjusted Future Returns	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Intercept	0.089541	3.91***	0.018438	1.55	0.005401	0.81
ANA	0.042633	3.20***	0.035842	4.62***	0.016322	3.34***
ANA*FD	**-0.04467**	**-2.46****	**-0.03566**	**-3.74*****	**-0.00878**	**-1.39**
CI	0.033388	1.74*	0.02041	2.03**	0.014827	2.66***
CI*FD	**0.043456**	**1.74***	**0.023152**	**1.87***	**0.020047**	**2.75*****
TI	0.016383	1	0.021383	2.29**	0.014463	2.6***
TI*FD	**-0.02555**	**-1.27**	**-0.02148**	**-1.90***	**-0.00849**	**-1.21**
FD	0.035438	1.93*	0.034552	3.35***	0.011778	1.88*
BEME	-0.01534	-5.7***	-0.00613	-4.98***	-0.00321	-4.85***
SIZE	0.019986	2.64**	0.017023	4.63***	0.011471	5.62***
MOM6RET	-0.00156	-3.17***	-0.0008	-2.79***	-0.00037	-2.01**
MOM7RET12	0.029984	2.27**	0.05512	6.52***	0.025398	5.61***
TURN	-0.03268	-3.43***	-0.01795	-2.83***	-0.00609	-1.68
BETA	0.014981	2.33**	0.003096	1.08	0.00346	2

This table reports regressions of future size-adjusted buy-and-hold abnormal returns (SAR) on informed signals for analysts (ANA), corporate insiders (CI), and transient institutions (TI) as developed in Section IV.B. FD is a binary variable where firms in the post Regulation-FD era (2001-2006) are assigned a value of one, while firms in the pre Regulation-FD era (1994-2000) are assigned a value of zero. Panels A, B, and C report future SAR's at the 3, 6, and 12 month horizons, respectively. Size is taken as the log (Market Value of Equity) at the beginning of each quarter. Book-to-market is calculated as the log (Book Value of Equity/Market Value of Equity) at the start of each quarter. Momentum is controlled for as a prior 6-month return (MOM6RET), as well as a prior return in months seven through twelve (MOM7RET12). Beta is calculated using CAPM over a 36-month rolling window, while share turnover is calculated as the sum of volume over the trailing 6 months divided by total shares outstanding at the beginning of the period. Two-tailed statistical significance levels at 1%, 5%, and 10% are indicated as ***, **, and * respectively, based on t-statistics calculated with Newey-West autocorrelation consistent standard errors.

robustness to prior results using PIN, FERC, and IDELAY as interaction variables, and illustrate the reliance of each party's signal on a particular type of information.

VII. Predicted Effects of Regulation Fair Disclosure on Informed Signals

Reg FD was adopted by the SEC on October 23, 2000 in order to eliminate the release of selective disclosure by management, so as to reduce information asymmetries between smaller individual investors and professionals. The intent of the ruling was to obligate all publicly traded companies to disclose material information to all investors simultaneously, preventing managers from leaking information to analysts and institutions before a public disclosure, and decreasing the level of information asymmetry within the marketplace. Opponents of Reg FD, however, argued that if the disclosing of material information via public channels was costly, then Reg FD could have the unintended effect of decreasing the overall quantity of disclosures, thereby increasing the level of information asymmetry between informed and uninformed investors.

Overall, evidence on the effectiveness of Reg FD on disclosure and information asymmetry appears to be mixed. Sidhu et al. (2008), show that adverse selection costs measured from the bid-ask spread increased approximately 36% after the passing of Reg FD. Duarte et al. (2008) find that Reg FD increases firms' costs of capital by 10-19 basis points per annum. Wang (2007) documents that roughly half of the firms that rely on private earnings guidance as a path of disclosure replace such guidance with nondisclosure in the years following Reg FD. These studies imply an increase in information asymmetry in the post-FD era. Conversely, prior research by Francis, Nanda and Wang (2006) and Ke, Petroni, and Yu (2007) has studied the effects of Reg FD on analysts and transient institutional investors. These studies conclude that the passing of Reg FD reduces the magnitude and frequency of private disclosures from insiders to analysts and institutions, and implies that Reg FD is effective in curtailing information leakages from management to informed agents, resulting a more level playing field between institutions and individual investors.

One explanation for such paradoxical results could be as follows. Information asymmetries between professional and individual investors may be diminished after the passage of Reg FD, while information asymmetry between insiders and the remainder of market participants (both individual and professional investors) increases. I test this hypothesis directly, using the same design as prior tests in Sections VI. Specifically, if decreases in private disclosures result in an increase in information asymmetry between insiders and the other informed agents, I predict that the degree of insider dominance over institutions and analysts will increase in the post-FD era.

Using the same structural model as prior analyses, I assign a value of one to Reg FD over the years 2001-2006, and zero for all prior years. Control variables remain unchanged. I examine the interactions of the three informed parties with Reg FD over the three, six, and twelve month horizons and report my findings in Table 10. Overall results are consistent with my predictions. Most notably, insiders gain significant predictive power across all three time windows, with the effect being most pronounced at the 3-month horizon. On the contrary, the interaction coefficients for analysts and institutions are negative at all six horizons, and are highly significant ($p<0.01$) for analysts at 6 and 12 month windows. Overall, Reg FD appears consistent with the loss of overall information flow from insiders to outsiders, resulting in increased insider' predictive abilities at the expense of analysts' and institutions' signals.

VIII. Conclusion and Future Research Suggestions

In this paper, I contribute to the existing literature on information intermediaries. I focus on sell-side analysts, corporate insiders, and transient institutional investors, and analyze (1) the horizons over which each group impounds information into prices, (2) the circumstances under which each group remains most informative when the level of inter-party disagreement is high, and (3) the effects of differing informational environments with respect to firm and industry-specific information on the signal strength of analysts and insiders. Indirectly, my results are also likely to interest individual investors and money managers who trade by following "smart money" strategies, by offering insight into the interpretation of divergent signals from informed agents.

Overall, I find that the signals of analysts and institutions are predictive of future prices only over shorter horizons, with analysts only marginally informative and institutions being completely uninformative at a 12-month horizon. Conversely, the insider signal strengthens with the passing of time, and is strongest at 12 months. Both of these results are consistent with each group's environment influencing their investment philosophies, i.e. insiders being forced to act as contrarians due to litigation risk and trading constraints, and analysts and institutions acting as momentum investors due to incentives to generate trade and "window-dress," respectively.

Regarding disagreement among informed agents, my tests indicate that the insider buy signal is most dominant, particularly at the 12-month window, where the informativeness of their signal is equivalent to a full consensus buy. In all other scenarios, the disagreeing parties' signal is less predictive of future returns than the full-consensus group. Under disagreement, the informativeness of each group's signal is positively correlated with (1) the relative strength of its signal over the given time horizon and (2) the relative weakness of the two countervailing forces. Overall, the informativeness of deviating agents is highest for analysts and institutions at the 3 and 6 month periods, and for insiders at the 12 month period. The hierarchy among these three groups show that insiders' actions appear most informative in predicting returns, followed by analysts, and finally, transient institutions.

A more detailed look at analysts' and insiders' signals reveals stylistic differences in the processes by which each agent informs future prices. For example, the normally dominant insider signal can be rendered insignificant if stock prices are efficient with respect to idiosyncratic-level information. Conversely, analysts' signals appear to be bolstered when industry-level information diffuses slowly into market prices, thereby making market prices less efficient with respect industry information. These results illustrate that insiders (analysts) have primary advantages in either obtaining or assimilating firm (industry)-specific information, and that these comparative advantages have significant effects on the strength of each group's signal in forecasting future returns. My final analysis indicates that while Regulation-FD may have leveled the playing field between professional and individual investors by preventing insiders from leaking information to institutions, reduced levels of management disclosure from this rule appears to have increased the predictive power of insiders' actions in the post-FD regime. If this is the case, then an unintended consequence of Reg FD may be that the overall levels of firm-specific informativeness in stock prices may have decreased, resulting in higher and not lower overall levels of information asymmetry in the marketplace.

The documentation of inter-party disagreement itself should interest researchers attempting to learn the intricacies of the price discovery process. Such trimodal disagreement could have implications for market efficiency by implicitly suggesting that arbitrageurs may create their own limits-to-arbitrage by trading in non-concerted directions, thereby prolonging, rather than correcting market mispricings. If this is indeed the case, then it would be interesting to study how the divergence of opinion could impede the speed of arbitrage following public information releases. If news is released, and arbitrageurs issue conflicting signals, price may be slower in converging to value, thereby making market anomaly strategies (e.g. momentum, post-earnings announcement drift, accrual fixation) more profitable and more easily executable.

Another avenue for future research involves investigating how differences in each party's relative aversion for idiosyncratic risk may result in inter-party disagreement. Assuming that a firm's risk profile increases over time (e.g. due to restatement or acquisition of a higher-risk firm), how would each party react? Analysts may choose to downgrade a stock because their recommendations are primarily written for individuals who are impacted by idiosyncratic risk (Goetzmann and Kumar, 2007; Malmendier and Shanthikumar, 2007). Insiders are also likely to be undiversified individuals, and may choose to sell shares for diversification purposes. Conversely, transient institutions are more likely to be well diversified, and may choose to increase their holdings since their return/risk profile would not be adversely affected.

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